2004

# Deterministic and Stochastic Capacity Estimation for Fishery Capacity Reduction

James Kirkley
*Virginia Institute of Marine Science*

Catherine Morrison Paul

Dales Squires

*Marine Resource Economics*, Volume 19, pp. 271–294
Printed in the U.S.A. All rights reserved
0738-1360/00 $3.00 + .00


# Deterministic and Stochastic Capacity Estimation for Fishery Capacity Reduction

JAMES KIRKLEY
College of William and Mary
CATHERINE J. MORRISON PAUL
University of California, Davis
DALE SQUIRES
National Marine Fisheries Service

**Abstract** *Deterministic data envelopment analysis (DEA) and stochastic production frontier (SPF) models are alternative methods for estimating capacity in fisheries. Fishery managers should be aware of likely differences in the capacity estimates obtained from these approaches if such estimates are to be used to support capacity reduction programs. In this paper, we provide a comparative analysis of DEA and SPF capacity estimates for a variety of possible capacity concepts using a panel data set for 10 vessels in the U.S. Northwest Atlantic scallop fishery. We find that DEA capacity output measures are higher than corresponding SPF measures, but that the two approaches provide similar guidance about overall and even relative boat-specific capacity levels under certain circumstances. The variations that emerge suggest, in particular, that biases can arise from inferring capacity output at "efficient" production levels, which disregards customary and usual operating conditions.*

**Key words** Capacity, utilization, DEA, SPF, fisheries, efficiency.

JEL Classification Codes: Q22, O13.

## Introduction

In recent years, various international and national organizations have emphasized the importance of reducing excess capacity in fisheries. The United Nations Food and Agricultural Organization (FAO) has called on nations "to take measures to prevent or eliminate excess fishing capacity" to be "commensurate with the sustainable

---

James Kirkley is a professor at Virginia Institute of Marine Sciences, College of William and Mary, Gloucester Point, Virginia 23062, email: jkirkley@vims.edu. Catherine J. Morrison Paul is a professor in the Department of Agricultural and Resource Economics and the Giannini Foundation, University of California, Davis, California 95616, email: cjmpaul@primal.ucdavis.edu. Dale Squires is an economist at the U.S. National Marine Fisheries Service, Southwest Fisheries Science Center, P.O. Box 271, La Jolla, California 92038-0271, email: dsquires@ucsd.edu.
The authors are grateful for discussions with Rolf Färe, Shawna Grosskopf, Ted McConnell, Ivar Strand, John Walden, and participants at meetings of the FAO Technical Working Group on the Management of Fishing Capacity, the NMFS National Capacity Management Team, the NMFS Expert Panel on Capacity Utilization in Fisheries, and the U.S. Congressional Task Force on Investment in Fisheries. The authors are responsible for any errors. The conclusions are not necessarily those of the U.S. National Marine Fisheries Service. Support for James Kirkley provided by the College of William and Mary, School of Marine Science and The Reves Center for International Studies, Williamsburg, VA, and for Catherine Morrison Paul from the Giannini Foundation.

use of fishery resources," through a 30% reduction in fishing capacity for primary world species (FAO 1997, 1998). The U.S. National Marine Fisheries Service (NMFS) has stressed the importance of establishing guidelines to estimate and reduce excess capacity, with the stated strategic plan objective of eliminating overcapitalization in 20% of federally managed fisheries by 2005 (NMFS 2001).

Effectively dealing with excess capacity in a given fishery, however, requires both establishing the extent of the problem by estimating the magnitude of excess capacity, and determining how particular boats in the fleet contribute to this capacity, rather than arbitrarily imposing a particular capacity reduction. This provides a foundation for establishing programs to reduce excess capacity that enhance fisheries' overall economic performance without further exacerbating the problem.

Data envelopment analysis (DEA) is currently the most widely used method for estimating capacity in fisheries (Kirkley and Squires 1998), although stochastic production frontier (SPF) methods have also recently been applied to this problem (Kirkley, Morrison Paul, and Squires 2002). Both methods have their advantages and disadvantages, so neither is clearly preferable (Resti 2000; Reinhard, Lovell, and Thijssen 2000). In particular, DEA analysis does not easily disentangle noise from efficiency (it is deterministic rather than stochastic, so all noise is attributable to inefficiency),[1] or permit prediction of output responses to changes in input or stock levels or the underlying technology. SPF methods require assumptions about the functional form for the production technology and distribution of the one-sided "inefficiency" error term, and do not readily handle multiple (particularly zero-valued) outputs.

These issues about the "best" method for estimating the extent of excess capacity, as well as variations in capacity definitions used for each method, are crucial limitations for responding to capacity concerns because they imply a broad range of possible capacity estimates with different policy implications. A key step toward effectively addressing and accommodating capacity problems is establishing how different estimation methods and definitions affect empirical estimates of excess capacity and capacity utilization. In this paper, we thus posit a range of capacity output and utilization representations and estimate, summarize, and compare the resulting measures of capacity and their implications for capacity reduction at both the overall and individual vessel levels.

More specifically, we first discuss the conceptual basis for measuring capacity output and utilization to establish the extent of excess capacity for a fishery, and then present and illustrate alternative frontier approaches to characterizing and estimating such measures. We assess the sensitivity of estimated capacity measures to alternative definitions of the fixed factors; imputations of variable input levels corresponding to capacity output levels; and evaluations of the measures at maximum, optimal, or target levels of the inputs. We also examine the implication from the use of frontier models that inefficiency comprises part of the utilization issue, which disregards variations in factors such as skipper skill and its impact on the interpretation and application of the resulting measures.

We use a panel data set for 10 vessels operating in the U.S. Northwest Atlantic sea scallop fishery between 1987 and 1990 to illustrate the results of these alternative definitions, experiments, and estimation methods. Based on measures obtained from both SPF and DEA methods, we find that excess capacity estimates for these vessels vary according to specification and boat. The estimates of excess capacity are particularly high for the DEA specifications and when full efficiency is incorpo-

---

[1] DEA measures tend to overestimate capacity output in the presence of substantial noise or outliers (Holland and Lee 2002).

rated into the definition of capacity utilization. The overall implications for capacity reduction from the two methods are quite consistent for many of the experiments, especially when imputed efficiency is not imbedded in the capacity output ratios. Even for boat-specific comparisons, which are required for consideration of decommissioning schemes to reduce excess capacity, some consensus of the "best" and "worst" boats emerges from the estimates.

## The Conceptual Model

Excess capacity implies that there is too much capacity (capital or vessel power for a fishery) to efficiently produce (harvest) the observed output (catch) level $Y_O$. That is, there is too much idle capital and thus wasted resources in the fleet, given existing catch levels. In reverse, excess capacity can be interpreted as current output being too low to fully utilize the existing level of capital, or capacity base. These concepts are essentially dual to each other; the first is an input-oriented idea targeting non-optimal capital levels, and the second is output oriented.

Economists and policymakers have traditionally focused on the output side when measuring capacity and capacity utilization, especially for fisheries (Klein 1960; Färe, Grosskopf, and Kokkelenberg 1989; Dupont *et al.* 2002). Capacity output, $Y_C$, is defined as the maximum, optimal, or potential output producible from the existing capital stock or capacity (fixed input) base. Capacity utilization (*CU*) is then defined as the amount of output that potentially "could" be produced from the existing capacity, $Y_C$, compared to observed output, $Y_O$, expressed in ratio form as $CU = Y_O/Y_C$ to represent the proportion of the capacity base that is effectively utilized.

That is, if measured *CU* is 0.75, 25% of the capital stock is deemed "excess capacity," or idle relative to its optimal level, and capacity reduction of this amount would be required to reach full utilization. The inverse ratio $1/CU = CU_I = Y_C/Y_O$ (where I denotes inverse) indicates the amount output would need to increase to fully utilize the existing capacity. Such a measure, which is more commonly computed in the fisheries capacity literature, implies that if the full power of the existing vessels were unleashed on the fishery, the vessels would be able to take 1/0.75 = 1.33 times (33% more than) the existing catch for this example.

The primary problem involved in constructing this ratio is defining and measuring the economically or technologically "optimal" or "potential" output, $Y_C$. An economic optimum may be defined as the output level consistent with the point of tangency between the short-run cost curve (constrained by the existing capital or capacity level) and the long-run curve.[2] This implies, however, that cost minimization is the goal of the producer (fisherman in this case), which may not be an appropriate assumption. A technological optimum can instead be defined as the most output possible to produce (catch) given the existing input base, in terms of fully efficient output (on the production frontier) combined with the output response to the relaxation of an input constraint (such as if regulations were lifted, thus shifting the frontier). However, empirical application of this idea requires distinguishing a true technical maximum, such as the point where the marginal products of variable inputs are zero, from a feasible optimum that reflects economic motivations for behavior.

Although defining $Y_O$ initially seems much simpler, it also raises questions. For many purposes, actual output is the appropriate output level to compare with $Y_C$.

---

[2] See Morrison (1985) for one example of such an application.

However, depending on the methods used to measure $Y_C$, other baselines might be more appropriate for fisheries. For example, if a total allowable catch (TAC) is in place, or a target catch has been established, one of these levels may be a better comparison point if they differ from observed catch. Even more importantly in the context of efficiency-based measures of $Y_C$, one might think the appropriate comparison might be to imputed technically efficient (TE) output, $Y_{TE}$. That is, if measured $Y_C$ is based on efficiency models, such as DEA and SPF, it reflects not only the potential output level if constraints restricting observed output production were relaxed, but also the attribution of "efficient" or "best practice" output. If measured $Y_{TE}$ is not consistent with customary and usual operating procedures — for example it ignores unmeasured determinants such as skipper skill or practices that would not be affected by regulatory changes — it is not really feasible and should not be imbedded in the estimate of potential output increases to capacity levels.

To develop these ideas further, we need to be more specific about how frontier estimation of the production relationship allows us to measure the difference between observed output, $Y_O$, and potential output, $Y_{TE}$ or $Y_C$. Frontier methods, such as DEA and SPF, are designed to characterize and measure a production set frontier or boundary, by contrast to standard econometric methods that fit a production curve through data points. The standard representation of the production relationship or technology is a production function, which we can write for our purposes as $Y(\mathbf{K},\mathbf{V},\mathbf{S},\mathbf{R})$, where **K** is a vector of capital stock inputs comprising the capacity base (often expressed in terms of vessel characteristics); **V** is a vector of variable inputs (including days and perhaps crew and fuel); **S** are nondiscretionary stock inputs not directly under control of the vessel operator, even in the long run (such as the biomass stock); and **R** is a vector of external control or shift variables (like year and season).[3]

Empirically estimating the production technology by frontier methods involves fitting the production function to the data points representing observed output-input combinations by "enveloping" the data to keep the observations within the frontier. Programming-based deterministic DEA methods construct a piecewise linear frontier around all the observations, and econometric-based stochastic SPF methods estimate a differentiable (smooth) frontier allowing for white noise. Observations that lie within the frontier are, therefore, considered "inefficient," given the measured production determinants, and the implied technically efficient output, $Y_{TE}$, is imputed by a radial expansion (line in two-dimensional space) from the origin to the frontier through the data point.

The efficiency "score" for each observation identifies the amount that output would have been greater if production had been fully (technically) efficient; $Y_{TE}/Y_O \geq 1$ measures this potential proportional expansion. This one-sided efficiency gap is often interpreted as deriving, at least in part, from unobserved observation-specific factors such as management (in this case skipper) skill or specific capital (vessel) characteristics. More random un- or mis-measured factors, such as weather, will instead be captured as noise if the model is estimated by stochastic methods. Given these potential estimation error terms, actual ($Y_O$) rather than "efficient" ($Y_{TE}$) output may more appropriately represent feasible production under customary and usual operating conditions.

---

[3] For many fisheries, multiple species are caught. This is particularly important to explicitly represent if certain target species are the focus of policy implementation. Pursuing this requires extending these ideas to a distance or transformation function model, as in Orea, Alvarez, and Morrison Paul (2004) or Felthoven and Morrison Paul (2004). This involves including ratios or levels of other outputs on the right-hand side of the function, respectively, but is otherwise similar to the production function approach. This is not a key issue for our current application, however, so we do not emphasize this issue further.

Although frontier methods are designed to measure $Y_{TE}$, they can be adapted to represent $Y_C$ by identifying how output production would be expected to further expand if specific rigidities (such as regulations) constraining observed behavior were lifted. Since direct output regulations in a fishery, such as limited fishing periods or a TAC, may be represented as restrictions on the number of days fished,[4] $Y_C$ may be defined as in Kirkley and Squires (1998), Dupont *et al.* (2002), and Kirkley *et al.* (2001) as the amount of fish that could be harvested if days were "unconstrained," given the existing capacity base (vessels). That is, if days fished is a component of the **V** vector ($V_D$ = days), $Y_C$ is the potential output level with unrestricted $V_D$ given all other production characteristics and the output maximization behavior underlying the primal model, and the implied fully utilized or capacity number of fishing days may be denoted $V_{D,C}$. Such a characterization of capacity output and utilization has been called "technological-economic" if its measurement is based on observed catch levels by vessels in the sample and, thus, is implicitly consistent with economic motivations (Kirkley *et al.* 2001).

In the DEA framework, $Y_C$ and $V_{D,C}$ are typically imputed by solving a linear programming problem without days included as a constraining input. In the SPF framework, the production relationship may similarly be estimated econometrically with days omitted as an argument of the production function.[5] Alternatively, however, one might think the potential or optimum number of fishing days, and associated output, may be defined according to the maximum number of days observed in the data or the point where the marginal product of additional days drops to zero. If other catch determinants, such as biomass stock levels, are also recognized as constraining inputs, one might wish to determine how changes in these conditions could affect potential output through similar experiments based on these arguments of the production function. Measuring these various aspects of capacity and capacity utilization requires choosing an estimation method that facilitates carrying out such experiments to generate a range of capacity indicators.

## Formalizing and Implementing the Framework

The two approaches we use for estimation of capacity output and utilization, deterministic data envelopment analysis (DEA) and stochastic production frontier (SPF) methods, are discussed in great depth in the efficiency literature and so will just be summarized briefly here.[6]

### *The DEA Model*

DEA is a nonparametric programming technique to solve a production maximization problem given a set of constraints (Charnes *et al.* 1994), which was extended to the calculation of capacity utilization by Färe, Grosskopf, and Kokkelenberg (1989) and Färe, Grosskopf, and Lovell (1994), and proposed for CU measurement in fisheries

[4] For some applications, rather than just unconstraining days, all variable inputs are unconstrained, based on the idea that if all choices were unrestricted they would change.

[5] Although this results in omitted variables bias for the implied input marginal products, the measures still appropriately represent the maximum potential output level given the levels of all other arguments of the function. See Kirkley, Morrison Paul, and Squires (2002) for further discussion.

[6] See Coelli, Rao, and Battese (1998) for an excellent overview of these methodologies and references to many more detailed and rigorous studies. Cooper, Seiford, and Tone (2000) and Kumbhakar and Lovell (2000) provide additional information about DEA and SPF applications, respectively.

by Kirkley and Squires (1998). The DEA approach to capacity measurement solves for the maximum output possible, given **K**, **S** levels and the existing production technology, with the variable factor(s) unconstrained. This capacity output level is solved for using linear programming procedures and is interpreted as the output that could be produced with full and efficient utilization of the variable input(s), given the capacity base.

Formally, following Färe, Grosskopf, and Kokkelenberg (1989), consider an industry producing a scalar output $Y^j$ using a vector of $n = 1,...N$ inputs $\mathbf{Z}^j$, where, for each $j$, $Y^j > 0$ and $\Sigma_n Z_n^j > 0$, and for each $n$, $\Sigma_j Z_n^j \geq 0$. That is, it is assumed that all firms produce at least some output and use some input, and each input, n, is used by some firm, $j$.

The capacity output definition offered by Johansen (1968), "...the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of variable factors of production is not restricted," can be solved from the output-oriented DEA problem for a particular time period, $t$, with **Z** divided into fixed (**K**,**S**) and variable (**V**) inputs:

$$\max_{\theta,\lambda,\mu} \theta, \quad \text{s.t.} \quad \theta Y^j \leq \sum_j \lambda^j Y^j, \sum_j \lambda^j K_k^j \leq K_k^j, k \in K, \qquad (1)$$
$$\sum_j \lambda^j S^j \leq S^j, \sum_j \lambda^j V_n^j = \mu_n^j V_n^j, n \in V,$$

where $\Sigma_j\lambda^j = 1.0$, $\lambda^j \geq 0$, for all $j$, $\mu_n^j \geq 0$ for $n \in \mathbf{V}$, S is a scalar **S** component (the biomass stock), and the $\lambda^j$ define the reference technology. The convexity constraint, $\Sigma_j\lambda^j = 1.0$, allows for variable returns to scale (Coelli, Rao, and Battese 1998), and the constraint, $\Sigma_j\lambda^j V_n = \mu_n^j V_n^j$, ensures that the variable inputs do not limit output.[7]

The parameter $\theta \geq 1$ represents a combination of output expansions to reach both technically efficient and capacity production. That is, it captures the potential (radial) increase in output, $Y_C/Y_O$ (with the $j$ superscripts suppressed for notational simplicity), if firm j operates efficiently given the observed levels of fixed factors (**K**, $S$) but without variable input constraints (full utilization of the variable inputs, **V**). The solved value of $\mu_n^j$, in turn, measures the "variable input utilization rate" — the ratio of the $n$th variable input level required to produce the capacity output divided by the actual level, $V_{n,C}/V_n$.[8]

Because the deviation between $Y_C$ and $Y_O$ embodies efficient (frontier) output production, the implications for potential output levels may be biased upward if measured "inefficiencies" are inherent in customary and usual operating procedures. So, to more appropriately represent true capacity utilization, the $Y_C$ estimate might better be compared to an estimate of efficiently produced output, $Y_{TE}$, from a corresponding DEA model with variable input use recognized as a constraining factor.

Such a $Y_{TE}$ measure, that is restricted by (corresponds to) observed variable input usage, is estimated by solving the linear programming problem:

---

[7] Coelli, Grifell-Tatje, and Perelman (2001) refer to this capacity output definition as the weak Johansen concept of capacity, because the solution to (1) reproduces output levels that are consistent with full utilization of the variable inputs but constrained by the fixed factors.

[8] The variable input utilization rate measures the ratio of optimal variable input usage ($\mathbf{V}_C$, corresponding to capacity output) to actual variable input usage (Färe, Grosskopf, and Lovell 1994). If the ratio of $\mathbf{V}_C$ to the observed variable input level **V** (or $V_{n,C}$ compared to $V_n$ for variable input $n$) exceeds 1.0, there is a shortage of this input, and the firm should expand use of the input. If the ratio is less than 1.0 there is a surplus, and the firm should reduce the use of the variable input.

$$\max_{\theta,\lambda} \theta, \text{ s.t. } \theta Y^j \le \sum_j \lambda^j Y^j, \sum_j \lambda^j Z_n^j \le Z_n^j, \tag{2}$$

$$\text{for all } n \ (n \in \mathbf{K},\mathbf{S},\mathbf{V}), \text{ and } \lambda^j \ge 0, \text{ for all } j,$$

where the input vector **Z** includes the **V** components, by contrast to equation (1). Solutions to equations (1) and (2) can be used to construct an unbiased excess capacity estimate, $CU_I = Y_C/Y_{TE}$.[9]

The notion of "unconstraining" the variable inputs to generate a measure of $Y_C$, as in equation (1), as opposed to $Y_{TE}$ from equation (2), has been used for most existing DEA applications of production models to capacity measurement for fisheries. However, other experiments that may be of interest for expanding our understanding and interpretation of capacity patterns are not as naturally carried out with this model. For example, it is not possible to define the optimal (full utilization) number of days by examining the marginal product curve for this input, because the functional relationship is not explicit for this deterministic framework. Similarly, evaluating the production relationship for alternative input levels may not prove fruitful, depending on the binding constraints on the estimates. If we wish to evaluate capacity output levels for alternative optimal or target levels of days or biomass stocks, we must solve the programming problem on a per-day or per stock-unit basis and then extrapolate by multiplying by the specified number of days or stock level. If outliers are holding out the frontier, this can generate unreasonable estimates of potential output.[10]

### *The SPF Model*

To facilitate carrying out such experiments and provide a comparison for DEA measures, we can turn to stochastic models that allow for randomness (which is inherent in fisheries production), and generate parameter estimates that reflect the general shape of the production relationship. One such approach is to apply SPF methods, that involve econometric estimation of $Y(\mathbf{K},\mathbf{S},\mathbf{V},\mathbf{R})$ by contrast to the deterministic DEA framework, but are still designed to represent efficient production (a production frontier).

A functional form assumption must be made for econometric implementation of a production model, but a flexible form limits the restrictions on the estimates imposed by the assumption. Thus, we initially assume $Y(\mathbf{K},\mathbf{S},\mathbf{V},\mathbf{R})$ may be approximated by a second-order logarithmic (translog) function:[11]

$$\begin{aligned}
\ln Y^{j,t} &= \alpha_0 + \sum_k \alpha_k \ln K_k^{j,t} + \alpha_S \ln S^{j,t} + \sum_n \alpha_n \ln V_n^{j,t} + \sum_r \alpha_r R_r^{j,t} \\
&+ \sum_k \gamma_{kS} \ln K_k^{j,t} \ln S^{j,t} + \sum_k \sum_n \gamma_{kn} \ln K_k^{j,t} \ln V_n^{j,t} + \sum_k \sum_r \gamma_{kr} \ln K_k^{j,t} R_r^{j,t} \\
&+ \sum_n \gamma_{Sn} \ln S^{j,t} \ln V_n^{j,t} + \sum_r \gamma_{Sr} \ln S^{j,t} R_r^{j,t} + \sum_n \sum_r \gamma_{nr} \ln V_n^{j,t} R_r^{j,t} \\
&+ 0.5 \sum_k \sum_l \beta_{kl} \ln K_k^{j,t} \ln K_l^{j,t} + 0.5 \sum_n \sum_m \beta_{nm} \ln V_n^{j,t} \ln V_m^{j,t} + 0.5 \sum_r \sum_s \beta_{rs} R_r^{j,t} R_s^{j,t},
\end{aligned} \tag{3}$$

---

[9] This is consistent with the "unbiased" CU ratio of technical efficiency scores associated with $Y_{TE}$ and $Y_C$ measures suggested by Kirkley *et al.* (2001).

[10] For example, if there were outlier observations for which estimated stock levels were very low but output was high, this will inflate the imputed $Y_C$ measures to unreasonable levels.

[11] Dummy variables for the boats, or fixed effects, were also included initially but were very insignificant, likely due to other boat-specific variables, such as the capital components.

across $j = 1 \ldots J$ firms and $t = 1, \ldots T$ time periods, where $(n,m)$, $(k,l)$, and $(r,s)$ index the components of the **V**, **K** and **R** vectors, respectively, and $S$ is a scalar.

This functional form embodies a full set of interactions among the arguments of the production relationship. For example, the components of the **R** vector are production function shifters, with the direct impact of the shift represented by $\alpha_r$ for factor $R_r$.[12] But the full impact of a change in $R_r$ might be dependent on other arguments of the function. The implied input-specific differences in the impacts are reflected by cross-terms, such as $\gamma_{kr}$, which indicates how a different $K_k$ level affects the impact of $R_r$ on $Y$.

For a particular application, however, these terms may be uninformative, particularly for variables that are either qualitative or do not vary by firm (boat). Accordingly, for our application interaction terms for the boat-specific **K** components were omitted, along with others that were invariably insignificant in preliminary estimation, resulting in the estimating equation:

$$\ln Y = \alpha_0 + \sum_k \alpha_k \ln K_k + \alpha_S \ln S + \sum_n \alpha_n \ln V_n + \sum_r \alpha_r R_r + \sum_n \gamma_{Sn} \ln S \ln V_n \quad (4)$$
$$+ \sum_r \gamma_{Sr} \ln SR_r + \sum_n \sum_r \gamma_{nr} \ln V_n R_r + \sum_n \beta_{nn} (\ln V_n)^2 + \sum_r \beta_{rr} R_r^2,$$

(where the boat and time period superscripts are now suppressed for notational simplicity).

Estimation of equation (4) by SPF methods, as initially developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), involves adding an error term to equation (4) that combines a one-sided "technical inefficiency" error, $-u$, and a standard "white noise" error, $v$ (*e.g.*, from measurement error and unobserved inputs). The $-u$ are assumed to be nonnegative random variables independently distributed as truncations at zero of $N(0, \sigma_u^2)$. The v are assumed to be independently and identically distributed random variables, $N(0, \sigma_v^2)$. Estimation of the resulting estimation equation to measure $Y_{TE}$ is then carried out by maximum likelihood methods.[13] Associated $Y_C$ measures, with variable inputs unconstrained, are obtained by eliminating the **V** arguments of the function and re-estimating (4) as $Y$(**K**,**S**,**R**).

Alternatively, it is possible to evaluate the model at other levels of the input variables, such as the maximum observed number of days (per boat) if that is deemed a likely "optimum" or potential level of fishing days in the absence of regulatory restraints. Implementing this procedure involves recognizing, as in Coelli, Perelman, and Romano (1999), that $Y_{TE}$ measures with "environmental" conditions included as arguments of the production technology represent net efficiency. Imputing gross efficiency measures inclusive of these conditions requires re-evaluating the model with the control variables replaced by the alternative values.[14]

In the fisheries context, this also implies that we may evaluate $Y_{TE}$ conditional

---

[12] These variables are not expressed in logarithms because they are qualitative variables, or time counters.

[13] See Coelli (1995) and Battese and Coelli (1995) for further elaboration of this literature and discussion of appropriate maximum likelihood estimation with panel data.

[14] This was accomplished by fitting the production technology based on the estimated parameters from the efficiency model, and using the residuals from that model compared to those from the estimated model to recompute a technical efficiency score based on the expression for the conditional expectation of $\exp(-u_{it})$ given $v_{it}$. The computations were done in EXCEL, using a distribution function for a standard normal random variable and the formula for the conditional expectation of the TE term from Battese and Coelli (1995), and Coelli, Rao, and Battese (1998).

on the size and composition of the resource stock and compare these measures to those obtained if resource abundance were unconstrained or at its maximum observed or target levels.[15] This generates $Y_C$ measures with somewhat different definitions but complementary interpretations, consistent with experiments suggested by NMFS (2001), that are relevant for resource managers seeking information about capacity output for the purpose of reducing overall harvesting capacity and achieving longer-term harvest goals.

## *Levels of Fisheries Analysis: Boat, Trip, Year, Fleet*

Capacity utilization measures derived from either DEA or SPF models, if computed on a per-boat basis, may be used not only to determine the output producible from the existing vessels or fleet but also to provide implications for limiting capacity through vessel reduction programs. An approximation to the amount the existing capacity (**K**) base would need to be contracted to produce a given output at full utilization may be obtained as the inverse of the output-oriented $Y_C/Y$ ($Y = Y_O$ or $Y_{TE}$) measure, CU = $Y/Y_C$. Although this generates useful information about the average fleet contraction required for efficient catch of existing or desired harvest levels, boat-level analyses should be carefully undertaken due to unmeasured technological and environmental conditions that may convolute boat-specific comparisons.

This application of capacity measures also raises questions about aggregation, or the level of the analysis. The types of capacity measures summarized above correspond to different circumstances that could face the fishery. If estimated at the trip level (as in our empirical illustration and most of the existing literature), they reflect per-trip measures for the boats in the data sample. However, for many policy concerns the implications for yearly output production, or for the entire fleet rather than by vessel, are central questions.

To move to these levels, we need to consider issues such as the feasibility of boats maintaining the number of fishing days on a yearly basis that are implied by the trip-level analysis. This may be accomplished by limiting the number of days per boat per year implied by the $\mathbf{V}_{D,C}$ estimates. Further, addressing questions about fleet capacity involves imputing capacity output values for boats in the fishery (fleet) but not in our sample, and, in turn, what would happen if all boats with the potential to enter the fishery did so (latent capacity). Although the universe of potential participants is difficult to establish due to the great mobility of vessels, we may infer this by attributing the capacity catch levels of active participants to the partially or fully inactive participants.

At the fleet level we can also compare our estimated capacity output production levels to a target output level for the fishery as a whole. Target output levels have been defined as the "maximum amount of fish over a period of time (year, season) that can be produced by a fishing fleet if fully utilized, while satisfying fishery management objectives designed to ensure sustainable fisheries." This implies a regulatory- or biologically determined "optimum" output, perhaps corresponding to the maximum sustained yield, to which fleet-level $Y_C$ may be compared to impute excess capacity relative to desired rather than observed output levels (FAO 1998). Measures using such a target level as the reference point indicate the extent of excess capacity compared to long-run optimal circumstances, as perceived by the fishery manager.

---

[15] As per Coelli, Perelman, and Romano (1999) this means that "all firms are compared with the frontier associated with the most favorable environment."

## Empirical Illustration: The U.S. Northwest Atlantic Sea Scallop Fishery

### *Data and Definitions of the Variables*

The U.S. Northwest Atlantic sea scallop (*Placopecten magellanicus*) fishery has traditionally been one of the most important U.S. fisheries in terms of vessel revenues. This scallop is harvested primarily from Georges Bank and various mid-Atlantic resource areas. The dominant gear type is the dredge, although small quantities are harvested with a trawl net. The primary landed product is meats after at-sea processing (shucking); only small quantities of sea scallops are landed in the shell. The fleet is mostly comprised of vessels that are 51 or more gross registered tons (GRT) in size.

Our data contains trip-level observations from 1987 to 1990, for ten scallop vessels that had relatively homogeneous characteristics and faced identical economic and environmental conditions. However, the number of days overall and per trip both varied significantly over the data sample, as is evident from the data summary in Appendix table A1.[16] The average number of days per year per vessel varied from a low of 112 for vessel 4 in 1987, to a high of 285 days for the same vessel in 1990, with an average of 248.5. The number of fishing days per trip varied from 3 to 26, and crew sizes ranged from 7 to 15. On the average trip in our sample, catch was 9,117 pounds of scallop meats, the trip took 15.5 days and had approximately 10 crew, and the boat had an engine horsepower of 540 and a dredge width of 14.5 feet.

The information in our panel data used to define our $Y$, $\mathbf{K}$, $\mathbf{V}$, $\mathbf{S}$, and $\mathbf{R}$ variables is obtained directly from settlement sheets. Our $Y$ measure is aggregate output (which is justifiable because the output is reasonably homogeneous), defined in terms of pounds of shucked scallop meat landed per trip.[17] Our fixed $\mathbf{K}$ input stocks are defined in terms of vessel characteristics representing capital heterogeneity — GRT ($K_G$), engine horsepower ($K_H$), and dredge width in feet ($K_D$) — rather than aggregating them into a summary capital measure.[18] Our main $\mathbf{V}$ component is fishing effort, expressed in terms of days at sea, as is common in the fisheries literature. Other more specific input measures may also appear as components of $\mathbf{V}$, but crew numbers tend to be relatively fixed for a particular boat and fuel data are not available (as is typical for such data). Thus, we initially specified crew, $V_C$, as an additional variable input, but ultimately treated it as a control variable because it did not seem a binding constraint. The biomass stock, which affects (and is affected by, for the fishery overall) vessel catch but is not directly under the control of any individual vessel captain, is our single $\mathbf{S}$ vector component.[19] Our stock abundance ($S$) measure is a fishery-dependent variable expressed in terms of the geometric mean of the number of baskets per standard tow (60 minutes) by vessels fishing the same

---

[16] Some additional information on the time dimension of these measures, as well as a more detailed definition and motivation of the models used here for analysis, can be found in Kirkley, Morrison Paul, and Squires (2002).

[17] If multiple species are caught, one must consider how to aggregate them, or whether it might be more appropriate to characterize a multiple output production relationship such as a distance function (Felthoven 2002). The relative homogeneity of our output supports our aggregated $Y$ measure, but this does ignore factors such as the size of the product or seasonal differences that might have quality implications.

[18] GRT ($K_G$) was ultimately omitted from the econometric analysis because it was too closely correlated to horsepower ($K_H$) for the effects to be identified separately.

[19] The captain selects when and where to fish, but since the choice is always to find the place with the highest stock level, production is still constrained by what is actually found.

geographic area during the same period of time.[20,21] The external conditions we use for **R** components are year and month counters.

### *The Results*

Our base capacity and input utilization measures are the implied ratios of potential (full utilization) to observed or efficient levels of output and days, $Y_C/Y_O$, $Y_C/Y_{TE}$, and $V_{D,C}/V_D$, provided in tables 1D and 1S for our DEA and SPF models, respectively. These ratios suggest that if the boats in our sample were operating at full technical efficiency given all inputs, including days, average output could have increased by nearly 20% ($Y_{TE}/Y_O = 1.19$) according to the SPF computations, but by almost 60% ($Y_{TE}/Y_O = 1.57$) based on the DEA model. As one would expect, the deterministic framework that attributes all variations to inefficiency, rather than noise in the data, results in a higher estimated frontier. As discussed in previous sections, however, this efficiency component of "potential" output may be attributed to customary and usual operating procedures and thus not be an appropriate base for imputing true capacity catch.

Recognizing the possible bias from convoluting efficiency and capacity significantly reduces the differences between the SPF and DEA measures. The SPF $Y_C$ measure with $V_D$ unconstrained (left out of the functional relationship), denoted $Y_{C,V}$, is, on average, 33% higher than that producible with full technical efficiency, $Y_{TE}$, and 57% greater than observed output, $Y_O$.[22] With DEA these numbers are 22% for $Y_{C,V}/Y_{TE}$, versus almost double (a 91% increase) for $Y_{C,V}/Y_O$. The former is more closely comparable to the corresponding SPF measure, because the bias from attributing mis-measured efficiency factors to CU is reduced when $Y_{TE}$ is used as the comparison base, thus reducing the impacts of outliers by including their effects in both the numerators and denominators of the ratios.[23] The remaining ratios presented in the tables are, therefore, expressed in terms of $Y_{TE}$.[24]

---

[20] The stock information was obtained from a resource monitoring program conducted between 1987 and 1995. The purpose of the resource monitoring program was to obtain information necessary to determine the gametogenic cycle, age and growth, resource abundance, and density. Approximately 50 vessels participated in the data collection program, and approximately 300 samples were obtained each year. Captains were requested to make one last tow for research purposes. They were asked to record loran readings, depth, surface temperature, dredge size, tow speed, and total catch (in bushel baskets), and to provide 1-6 baskets of shell stock (live scallops in the shell) to the researchers. Resource abundance was estimated by taking the geometric mean of catch per unit effort (CPUE) of all trips by vessels fishing the same geographical areas during the same period of time and using the same dredge size (this is further discussed in Kirkley, Squires, and Strand 1995).

[21] There has been considerable debate about the appropriateness of using catch per unit effort (CPUE) or landings per unit effort (LPUE) to indicate stock abundance or density (Dickie 1955; Paloheimo and Dickie 1964; Westerheim and Foucher 1985; Pennington 1986; Richards and Schnute 1986; and Hilborn and Walters 1992), but there are numerous reasons why these may not be adequate indicators (Kirkley, Squires, and Strand 1995). Moreover, Dickie (1955, p. 805) suggested that average catch per vessel per trip may be a valid indicator of the relative abundance of sea scallops. Our average tow measure, thus, seems a relatively justifiable stock indicator, although as pointed out by an anonymous referee, it is possible that local density at the end of a trip does not reflect the overall density of the trip.

[22] When $V_C$ is also unconstrained, the estimates are statistically equivalent, suggesting that crew is essentially a fixed input.

[23] The DEA measure might even slightly understate potential output relative to the base in the $Y_{C,V}/Y_{TE}$ experiment, due to the high $Y_{TE}$ estimate for such a deterministic model.

[24] Note also that the $Y_{C,V}/Y_{TE}$ measures presented in tables 1S and 1D are computed in terms of ratios of the average output measure. If these measures are constructed as averages of the CU ratios instead of ratios of the averages, they are even more significantly biased upward. Even for the SPF model they suggest that potential output is more than twice $Y_{TE}$, which results from outliers for observations where the actual days are exceedingly low. This emphasizes the importance of first averaging the potential output levels, and then taking ratios, although the reverse approach is sometimes used.

**Table 1D**
Ratios of Capacity to Base Catch Levels, Days per Trip, DEA Model

| | Total | Boat 1 | Boat 2 | Boat 3 | Boat 4 | Boat 5 | Boat 6 | Boat 7 | Boat 8 | Boat 9 | Boat 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Y_{TE}/Y_O$ | 1.57 | 1.50 | 1.14 | 1.57 | 1.62 | 1.52 | 1.61 | 1.39 | 1.61 | 1.73 | 1.73 |
| $Y_{C,V}/Y_O$ | 1.91 | 1.72 | 1.76 | 2.22 | 1.83 | 1.97 | 1.99 | 1.52 | 1.89 | 2.07 | 2.20 |
| $Y_{C,V}/Y_{TE}$ | 1.22 | 1.15 | 1.55 | 1.42 | 1.13 | 1.29 | 1.24 | 1.09 | 1.17 | 1.20 | 1.27 |
| $Y_{C,VS}/Y_{TE}$ | 1.32 | 1.24 | 2.01 | 1.51 | 1.24 | 1.39 | 1.29 | 1.18 | 1.23 | 1.35 | 1.37 |
| $Y_{C,VSK}/Y_{TE}$ | 1.39 | 1.24 | 2.84 | 1.73 | 1.24 | 1.62 | 1.35 | 1.18 | 1.31 | 1.35 | 1.42 |
| $Y_{VDMax}/Y_{TE}$ | 2.33 | 2.49 | 2.50 | 1.91 | 2.44 | 1.74 | 2.59 | 2.23 | 2.37 | 2.48 | 2.53 |
| $Y_{VCOpt}/Y_{TE}$ | 1.74 | 1.86 | 1.87 | 1.43 | 1.83 | 1.30 | 1.94 | 1.67 | 1.77 | 1.86 | 1.89 |
| $Y_{VCMax}/Y_{TE}$ | 1.63 | 1.59 | 1.38 | 1.65 | 1.56 | 1.65 | 1.66 | 1.69 | 1.64 | 1.60 | 1.64 |
| $Y_{SMax}/Y_{TE}$ | 4.90 | 4.61 | 1.60 | 2.89 | 5.06 | 2.99 | 5.03 | 4.84 | 5.22 | 6.70 | 6.72 |
| $*Y_{SMax}/Y_{TE}$ | 1.60 | 1.45 | 1.23 | 1.71 | 1.46 | 1.65 | 1.59 | 1.44 | 1.62 | 1.74 | 1.84 |
| $Y_{STar}/Y_{TE}$ | 6.43 | 6.05 | 2.11 | 3.80 | 6.65 | 3.93 | 6.61 | 6.36 | 6.86 | 8.81 | 8.82 |
| $*Y_{STar}/Y_{TE}$ | 2.11 | 1.90 | 1.62 | 2.25 | 1.92 | 0.22 | 2.08 | 1.90 | 2.13 | 2.28 | 2.42 |
| $Y_{C,V}/Y_{TE}$ optdays/trips | 1.41 | 1.31 | 1.85 | 1.61 | 1.25 | 1.50 | 1.45 | 1.31 | 1.37 | 1.43 | 1.45 |
| $Y_{C,VS}/Y_{TE}$ optdays/trips | 1.63 | 1.45 | 4.03 | 1.85 | 1.40 | 1.77 | 1.61 | 1.48 | 1.56 | 1.64 | 1.66 |
| $V_{D,C,V}/V_D$ | 1.23 | 1.17 | 1.57 | 1.39 | 1.13 | 1.27 | 1.27 | 1.08 | 1.21 | 1.23 | 1.29 |
| $V_{D,C,VS}/V_D$ | 1.23 | 1.17 | 1.93 | 1.34 | 1.13 | 1.24 | 1.27 | 1.08 | 1.21 | 1.23 | 1.29 |
| $V_{D,C,VSK}/V_D$ | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 | 1.19 |

* Observations were reduced from 581 to 535 when S was restricted to ≥ 1.25.

**Table 1S**
Ratios of Capacity to Base Catch Levels, Days Per Trip, SPF Model

| | Total | Boat 1 | Boat 2 | Boat 3 | Boat 4 | Boat 5 | Boat 6 | Boat 7 | Boat 8 | Boat 9 | Boat 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Y_{TE}/Y_O$ | 1.19 | 1.19 | 1.20 | 1.19 | 1.19 | 1.20 | 1.17 | 1.15 | 1.21 | 1.19 | 1.20 |
| $Y_{C,V}/Y_O$ | 1.57 | 1.47 | 2.57 | 1.81 | 1.49 | 1.55 | 1.64 | 1.28 | 1.55 | 1.59 | 1.74 |
| $Y_{C,V}/Y_{TE}$ | 1.33 | 1.23 | 2.15 | 1.52 | 1.25 | 1.30 | 1.40 | 1.11 | 1.28 | 1.33 | 1.45 |
| $Y_{C,VS}/Y_{TE}$ | 1.35 | 1.22 | 2.36 | 1.55 | 1.24 | 1.31 | 1.42 | 1.12 | 1.32 | 1.37 | 1.49 |
| $Y_{C,VSK}/Y_{TE}$ | 1.39 | 1.19 | 2.26 | 1.70 | 1.21 | 1.51 | 1.39 | 1.16 | 1.34 | 1.43 | 1.52 |
| | | | | | | | | | | | |
| $Y_{VDMax}/Y_{TE}$ | 1.55 | 1.43 | 2.51 | 1.80 | 1.41 | 1.57 | 1.58 | 1.30 | 1.51 | 1.55 | 1.71 |
| $Y_{VCOpt}/Y_{TE}$ | 1.22 | 1.15 | 1.92 | 1.40 | 1.13 | 1.23 | 1.25 | 1.08 | 1.18 | 1.21 | 1.32 |
| $Y_{VCMax}/Y_{TE}$ | 0.99 | 1.00 | 1.04 | 0.98 | 0.96 | 0.99 | 1.00 | 1.00 | 0.99 | 0.98 | 0.97 |
| $Y_{SMax}/Y_{TE}$ | 1.17 | 1.14 | 1.30 | 1.22 | 1.15 | 1.19 | 1.17 | 1.11 | 1.18 | 1.19 | 1.22 |
| $Y_{STar}/Y_{TE}$ | 1.31 | 1.25 | 1.42 | 1.38 | 1.31 | 1.33 | 1.30 | 1.20 | 1.31 | 1.35 | 1.40 |
| $Y_{VDSMax}/Y_{TE}$ | 1.71 | 1.58 | 3.27 | 2.04 | 1.46 | 1.74 | 1.80 | 1.43 | 1.68 | 1.64 | 1.85 |
| | | | | | | | | | | | |
| $Y_{C,V}/Y_{TE}$ optdays/trips | 1.49 | 1.37 | 2.28 | 1.70 | 1.48 | 1.14 | 1.57 | 1.20 | 1.39 | 1.53 | 1.60 |
| $Y_{C,VS}/Y_{TE}$ optdays/trips | 1.51 | 1.36 | 2.55 | 1.73 | 1.48 | 1.15 | 1.60 | 1.20 | 1.43 | 1.56 | 1.65 |
| | | | | | | | | | | | |
| $V_{D,C,V}/V_D$ | 1.26 | 1.21 | 1.82 | 1.33 | 1.21 | 1.23 | 1.32 | 1.10 | 1.25 | 1.28 | 1.33 |
| $V_{D,C,VS}/V_D$ | 1.28 | 1.19 | 1.95 | 1.36 | 1.20 | 1.24 | 1.33 | 1.11 | 1.27 | 1.32 | 1.37 |
| $V_{D,C,VSK}/V_D$ | 1.31 | 1.18 | 1.86 | 1.49 | 1.17 | 1.40 | 1.32 | 1.15 | 1.29 | 1.36 | 1.39 |

Further unconstraining the model to generate $Y_{C,VS}$, where the $VS$ subscript indicates that both $V_D$ (days) and $S$ (stock abundance) are omitted as functional arguments, suggests a limited stock impact within the confines of the observed data. The additional elimination of **K** constraints to generate $Y_{C,VSK}$, a measure conceptually similar to a peak-to-peak measure (a traditional concept sometimes used for capacity analysis, based on Klein 1960), also has little impact. That is, $CU_I = Y_C/Y_{TE}$ rises only from 1.33 to 1.35 and 1.39, respectively, for the SPF model, and from 1.22 to 1.32 and 1.39 for the DEA model for these experiments. This supports the notion that the primary constraint on production is the average days fished per trip.

These $CU_I$ measures imply corresponding full utilization increases in average fishing days of 26% ($V_{D,C,V}/V_D = 1.26$) when days are unconstrained, and of 28 and 31% when output is not conditioned on stock abundance and capital characteristics, respectively, for the SPF model. The DEA analysis suggests a similar increase of 23% when days alone or days and stocks are unconstrained, but only a 19% increase when **K** is also unconstrained (because relaxing constraints in the DEA framework implies higher output levels, so fewer days are required to realize a given output). These full utilization $V_D$ values, implying increases of 4–5 days/trip on average, fall well within the scope of the data.

This evidence may also be compared to measures from alternative experiments that evaluate potential output if days for all trips were at the maximum observed ($V_{DMax} = 26$), or the average of the optimum (fully utilized, $V_{DOpt} = 19.44$) number of days. For the SPF model, the resulting $Y_{C,VDMax}$ and $Y_{C,VDOpt}$ ratios imply potential increases of 55% and 22% over technically efficient output. The corresponding DEA values are more dramatic, which might be expected, since a diminishing marginal product is not embodied in the measures. They suggest a more than doubling ($Y_{VDMax}/Y_{TE} = 2.33$) of production at $V_{DMax}$, and a 74% increase at $V_{DOpt}$. If instead crew numbers were always at the maximum observed, $V_{CMax} = 15$, virtually no change in output is implied compared to technical efficient output for the SPF framework. Thus, $V_C$ does not seem a binding constraint or determining factor for capacity utilization, at least for the stochastic model, although for the DEA framework a 63% increase is implied at $V_{CMax}$.

By contrast, the impacts of stock abundance implied by the $Y_C$ measures evaluated at maximum (6.85) and target (9.0) $S$ levels, $Y_{C,SMax}$ and $Y_{C,STar}$, show that $S$ is a significantly binding factor, even for the SPF model, for $S$ levels well above average or beyond the scope of the observed data. On average, potential output $Y_C$ is 17% and 31% greater than $Y_{TE}$ in these two scenarios for the SPF specification, but for DEA the implied increases are nearly 5- and 6.5-fold, based on some trips where catch was high but measured abundance very low. If exceedingly low (perhaps irrelevant) outliers where $S < 1.25$ are dropped from the sample, the implied increases are instead 60% and slightly more than double.

Note also that these imputed values represent the effects on potential output of adapting only one factor. For comparison, the $Y_{C,VDSMax}$ ratios for the SPF model (such an experiment cannot be done with DEA) evaluate $Y_C$ with both $V_D$ and $S$ at their maximum levels. In this case the average potential increase in output would have been 71% instead of the 55% implied only by $V_{D,Max}$ and the 17% implied by $S_{Max}$; it is close to additive.

An important issue underlying the capacity estimates summarized so far (and typically estimated in the literature) is that when days per trip are unconstrained, the implied annual operating days per boat are not limited to a "reasonable" number. The next values presented in the tables impose a ceiling "optimal" number of yearly fishing days, and solve for the associated number of trips to derive the per-trip measure (denoted "optdays/trips"). The optimal days number used, optdays = 264, was computed as the days associated with the estimated maximum point on the total product curve, based on the annual per-boat data, and fell nearly halfway between the maximum of 285 and average of 248.5.

The $Y_C$ measures based on these computations were constructed by ordering the trips per year per boat in descending order according to the catch/day, and cumulating catch until the implied days reached 264. The resulting $Y_{C,V}/Y_{TE}$ measures imply an increase of 49 or 41% to capacity output, by contrast to the 33 and 22% increases implied on a trip basis without optdays imposed for SPF and DEA, respectively. Analogous measures with the stock level unconstrained indicate average potential increases of 51 and 63% over $Y_{TE}$, as contrasted to 35 and 32% without the optdays constraint, for the SPF and DEA models. Note, however, that although the imposition of "optdays" increases the estimated potential output level per trip, the measure is based on a smaller number of trips per year.[25]

These per-trip estimates may be better compared to target output estimates if translated into pounds of meats. For example, although not presented in the tables, the implied total pounds of scallop meats based on the total capacity output catch, $Y_{C,V}$, truncated at the optimal number of days, 264, is nearly 7.8 million pounds over the whole time period for the SPF framework — and up to 10.2 million pounds for the DEA analysis. This can be compared to the approximately 5.3 million pounds actually harvested, or 6.3 million pounds that implicitly could have been taken at full technical efficiency.

Finally, extrapolation to the full fleet and accommodation of latent capacity should be considered, because these boats comprise only a subset of the vessels operating in — or potentially entering — the fishery if conditions prompted such adjustments. Moving to the fleet level also facilitates comparison of the potential catch of the existing fleet to target catch levels.

Presently, there are approximately 175 full-time vessels operating in the Northwest Atlantic sea scallop fishery. In 1996, there were 82 vessels of the same size class (51 to 150 GRT) as those of the panel data set operating in the fishery, 132 vessels of the next size class (> 150 GRT), and 120 vessels of the smallest documented size class (5 to 50 GRT). If only the 82 vessels similar to those in the sample are considered, the capacity output of the resulting fleet would be between 17.7 and 23.3 million pounds per year, on average, if the boats operated 264 days a year (based on the $Y_{C,V}$ optdays/trips computation which seems the most representative of FAO capacity guidelines), according to the DEA and SPF estimates, respectively. This can be compared to the long-term sustainable catch estimated at approximately 20–29.3 million pounds of meats (Northeast Fisheries Science Center 1998, 1999) to show the extent of excess capacity (although it should be recognized that this comparison is analogous to comparing $Y_C$, which embodies full efficiency, with $Y_O$).

Perhaps an even more pressing fishery management question than the extent of overall capacity, however, is how one might use these types of estimates to guide capacity reduction programs such as a vessel decommissioning process. This requires determining the requisite number and composition of vessels to satisfy full utilization production goals at a target output level, to enhance the economic and biological performance of the fishery.

From this perspective, the question is how inputs may be reduced relative to a desired output level, such as a TAC, rather than the output expansion implied by full utilization of the existing capacity.[26] For example, if output from the observed **K** in our sample fleet could be expanded by a factor of 1.25–1.35, as broadly suggested

[25] If the yearly values are instead divided by the actual number of trips, the $Y_{C,V}/Y_{TE}$ and $Y_{C,VS}/Y_{TE}$ measures become 1.23 and 1.25 for the SPF model, and 1.22 and 1.41 for the DEA model, compared to 1.33 and 1.35 and 1.22 and 1.32 for the models without the optdays constraint.

[26] We will not focus on the formal mechanics and nuances of answering this type of question, but instead on the approximate implications we may obtain from the output-oriented estimates.

by our estimates, **K** could potentially be reduced by 20 to 25% (*e.g.*, CU = 1/1.25 = 0.8) and still produce the existing output level.[27]

In turn, boat level capacity estimates may be used to identify operating units (individual vessels or vessel size classes) that might most justifiably be decommissioned, with the goal of increasing overall efficiency and, thus, rents in the fishery. Care must be taken when doing comparisons at the boat level, however, where one would expect greater discrepancies across specifications and estimation methods than on average. Even if boat- or skipper-specific variations in technology or skill are accommodated by comparisons of $Y_C$ with $Y_{TE}$ measures, our primal measures do not reflect economic issues such as opportunity costs that fisheries managers should take into account for relevant policy development and implementation.

Keeping this qualification in mind, our capacity measures can be used to establish precautionary input levels by identifying specific groups of vessels that could yield maximum overall catch efficiency for a given TAC. A suggested ranking of operating units can be obtained by ranking observations by an efficient capital criterion such as boat-level $Y_{TE}$ or $Y_C$ per day, and summing the implied production of each unit until the total reaches the target.

Such per-day estimates and corresponding CU measures based on observed output ($Y_O/Y_{TE}$ and $Y_O/Y_{CU}$) are presented in tables 2D (DEA) and 2S (SPF).[28] Overall, the SPF measures suggest that the boats in our sample are producing at about 84% efficiency, and 80% of capacity on a per-day basis. So, technically efficient daily output is, on average, about 19% larger than observed, given other input levels and environmental conditions. This potential rises to 25% if based on estimated optimal days per trip. The corresponding numbers are 64% for both DEA experiments, suggesting that total output/day could have been about 56% greater than observed.

The boat-specific SPF efficiency (TE) scores $Y_O/Y_{TE}$ indicate that boats 2, 8, and 10 are producing the least, and boats 6 and 7 are the most efficient, although the variation is very small (from 0.83 to 0.87). For DEA, boats 9 and 10 are the worst, and boat 2 the best, followed by boat 7, with greater variation (0.58 to 0.88). If both technical inefficiency and low utilization are taken into account, based on $Y_{C,V}$, the SPF measures suggest that boat 2 was producing with the most excess capacity, at 0.71. The CU levels of boats 3 and 10 are just slightly higher, at 0.74 and 0.76. Boat 7 again appears the best, with an average CU ratio of 0.86. This contrasts to a DEA ranking of boats 9 and 10 with the lowest ratios (0.6 and 0.59), and boats 2 and 7 with the highest ratios (0.82 and 0.70).[29,30]

---

[27] Due to variable returns to scale, this is not completely appropriate here since these relationships are only directly inversely related with constant returns to scale. However, it will be a close approximation. Also, since the full input base is not well defined in fisheries, justifiable scale economy measures are difficult to generate, evaluating scale economies is problematic.

[28] The SPF numbers for table 2S were constructed as fitted output/day for each experiment, computed for each observation and then averaged. The DEA numbers for table 2D were re-estimated based on a per-day programming model.

[29] Note that the DEA efficiency and utilization measures are also much more similar on a per-day basis than are the SPF numbers. Potential output/trip increases when days are unconstrained, but the associated days/trip also rises, so this counteracts the upward shift on a per-day basis.

[30] Although we will focus on these numbers for our discussion, a variety of other values that may be of interest to fisheries managers are presented in the table. In particular, the ratios based on unconstraining $S$ and $K$ ($Y/Y_{C,VS}$ and $Y/Y_{C,VSK}$) are virtually identical to those with just days unconstrained for the SPF estimates, although the DEA estimates indicate greater excess capacity. The rankings remain broadly consistent across boats, although it appears that both stock and capital constraints are more binding for some (boats 2 and 4, and 2, 3, and 5, respectively). Also, because using DEA for this experiment requires estimating the model on a per-day basis and then extrapolating, the experiments with, for example, $S$ set at a target level, yield nonsensical results. $Y_{VD,\text{Max}}$ indicates the most per-day catch found for any boat for any time period. Then the other estimates relax constraints further, resulting in estimates beyond the range of any reasonable definition of "potential" output.

**Table 2D**
Catch Per Day — Actual, TE, and CU, DEA Model

| | Total | Boat 1 | Boat 2 | Boat 3 | Boat 4 | Boat 5 | Boat 6 | Boat 7 | Boat 8 | Boat 9 | Boat 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Y_O$ | 590.5 | 674.9 | 686.9 | 514.0 | 621.3 | 531.2 | 598.8 | 656.7 | 583.1 | 565.5 | 551.8 |
| $Y_{TE}$ | 926.5 | 1,010.6 | 779.5 | 805.7 | 1,005.1 | 806.8 | 963.5 | 913.5 | 937.3 | 978.3 | 952.6 |
| $Y_{C,V}$ | 917.4 | 976.1 | 842.0 | 830.6 | 991.8 | 820.5 | 934.2 | 940.7 | 916.2 | 944.8 | 941.8 |
| $Y_{C,VS}$ | 1,002.8 | 1,113.8 | 970.5 | 880.9 | 1,129.8 | 871.4 | 980.1 | 1,035.1 | 957.6 | 1,108.0 | 1,017.1 |
| $Y_{C,VSK}$ | 1,086.5 | 1,113.8 | 1,162.2 | 1,079.4 | 1,129.8 | 1,089.4 | 1,062.7 | 1,035.5 | 1,061.2 | 1,108.9 | 1,079.4 |
| $Y_{VDMax}$ | 1,280 | 1,568 | 740 | 840 | 1,585 | 825 | 1,435 | 1,372 | 1,342 | 1,439 | 1,362 |
| $Y_{VCMax}$ | 2,047 | 2,455 | 1,063 | 1,369 | 2,411 | 1,361 | 2,297 | 2,407 | 2,180 | 2,207 | 2,165 |
| $Y_{SMax}$ | 5,246 | 5,283 | 1,844 | 3,196 | 5,707 | 3,435 | 5,334 | 5,346 | 5,511 | 7,497 | 7,101 |
| $Y_{Star}$ | 6,892 | 6,941 | 2,423 | 4,199 | 7,498 | 4,513 | 7,008 | 7,024 | 7,241 | 9,850 | 9,330 |
| $Y_O/Y_{TE}$ | 0.64 | 0.67 | 0.88 | 0.64 | 0.62 | 0.66 | 0.62 | 0.72 | 0.62 | 0.58 | 0.58 |
| $Y_O/Y_{C,V}$ | 0.64 | 0.69 | 0.82 | 0.62 | 0.63 | 0.65 | 0.64 | 0.70 | 0.64 | 0.60 | 0.59 |
| $Y_O/Y_{C,VS}$ | 0.59 | 0.61 | 0.71 | 0.58 | 0.55 | 0.61 | 0.61 | 0.63 | 0.61 | 0.51 | 0.54 |
| $Y_O/Y_{C,VSK}$ | 0.54 | 0.61 | 0.59 | 0.48 | 0.55 | 0.49 | 0.56 | 0.63 | 0.55 | 0.51 | 0.51 |

**Table 2S**
Catch Per Day — Actual, TE, and CU, SPF Model

| | Total | Boat 1 | Boat 2 | Boat 3 | Boat 4 | Boat 5 | Boat 6 | Boat 7 | Boat 8 | Boat 9 | Boat 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $Y_O$ | 590.5 | 674.9 | 686.9 | 514.0 | 621.3 | 531.2 | 598.8 | 656.7 | 583.1 | 565.5 | 551.8 |
| $Y_{TE}$ | 700.5 | 802.9 | 824.1 | 612.3 | 738.4 | 635.6 | 699.8 | 754.4 | 703.3 | 674.1 | 663.0 |
| $Y_{C,V}$ | 737.9 | 821.4 | 972.1 | 697.7 | 761.6 | 668.3 | 744.5 | 759.7 | 724.6 | 699.9 | 721.7 |
| $Y_{C,VS}$ | 740.4 | 822.7 | 999.4 | 701.9 | 760.2 | 672.2 | 746.4 | 760.4 | 727.6 | 701.7 | 722.0 |
| $Y_{C,VSK}$ | 740.5 | 814.2 | 998.2 | 701.2 | 762.6 | 685.6 | 738.1 | 760.7 | 729.8 | 710.5 | 729.2 |
| $Y_{VDMax}$ | 681.0 | 767.9 | 804.9 | 626.3 | 719.0 | 615.0 | 672.0 | 736.8 | 674.8 | 645.7 | 661.4 |
| $Y_{VDOpt}$ | 691.4 | 802.5 | 858.9 | 601.6 | 707.4 | 629.2 | 699.1 | 755.5 | 698.0 | 657.3 | 642.1 |
| $Y_{VCMax}$ | 643.6 | 714.1 | 784.1 | 602.4 | 672.5 | 585.8 | 637.6 | 659.8 | 641.1 | 619.7 | 639.2 |
| $Y_{SMax}$ | 821.8 | 917.9 | 1,073.4 | 744.8 | 845.6 | 755.7 | 820.0 | 839.9 | 827.2 | 800.7 | 806.3 |
| $Y_{STar}$ | 919.4 | 1,006.1 | 1,167.3 | 845.6 | 970.3 | 844.5 | 907.6 | 907.5 | 924.1 | 910.9 | 925.5 |
| $Y_{VDSMax}$ | 711.1 | 790.0 | 1,021.2 | 681.6 | 697.6 | 648.5 | 723.3 | 727.1 | 715.7 | 656.4 | 692.4 |
| $Y_O/Y_{TE}$ | 0.84 | 0.84 | 0.83 | 0.84 | 0.84 | 0.84 | 0.86 | 0.87 | 0.83 | 0.84 | 0.83 |
| $Y_O/Y_{C,V}$ | 0.80 | 0.82 | 0.71 | 0.74 | 0.82 | 0.79 | 0.80 | 0.86 | 0.80 | 0.81 | 0.76 |
| $Y_O/Y_{C,VS}$ | 0.80 | 0.82 | 0.69 | 0.73 | 0.82 | 0.79 | 0.80 | 0.86 | 0.80 | 0.81 | 0.76 |
| $Y_O/Y_{C,VSK}$ | 0.80 | 0.83 | 0.69 | 0.73 | 0.81 | 0.77 | 0.81 | 0.86 | 0.80 | 0.80 | 0.76 |

The discrepancies between the models for boat 2 are by far the greatest; its performance seems poorest by the SPF and best by the DEA methods. It is difficult to assess why this is so, although this boat was an anomaly for this fleet in terms of vessel type (with low horsepower and a different type of hull, but a very competent captain, and dropped out of the fishery in 1987, the year with highest overall utilization). When it is left out of the sample the results are much more consistent, although not as closely related at this boat-specific level as for the overall averages.

If we used these estimates to motivate a decommissioning scheme, we would likely conclude from either framework that boat 7 should be ranked first as a contributor to efficient catch, with perhaps boat 1 following (although boat 6 appears better from the TE SPF estimates). In reverse, boat 10 and then perhaps boat 3 (or 9 if DEA is used alone) might be the first perused to see if they should be decommissioned (although the TE estimates suggest greater relative efficiency than utilization levels for boat 3). These implications from the CU measures are broadly consistent with the catch/day numbers, with boat 3 having the lowest catch/day, and boat 7 only a somewhat lower catch/day than boat 1.

Although the indicators of the "best" and "worst" performers conform quite closely across specification, the DEA and SPF models, as well as the $Y_{TE}$ versus $Y_C$ measures, provide quite conflicting rankings. There is negligible variation in the estimated ratios in the mid-range, however, especially for the SPF framework, so these discrepancies are not substantive; little guidance is generated from either method for ranking the middle boats.

Given these similarities in the vessel-specific estimated TE scores, we conducted tests of the equality of TE across specifications and among vessels (see Appendix table A2). Wilcoxon Signed Rank tests were used to test whether the mean TE scores derived from the DEA and SPF methods were equal, and were strongly rejected at any reasonable level of significance.[31] Kruskal-Wallis tests also rejected the hypothesis of equal mean TE scores for all 10 vessels (or with vessel 2 excluded) for both the SPF and DEA estimates at the 5% level of significance.[32] Additional tests were conducted over different groupings of vessels. After eliminating vessels 7 and 2, we were unable to reject the null hypothesis of the equality of mean SPF TE estimates of the remaining vessels at the 5% level of significance, but could reject the hypothesis for the DEA scores unless the level of significance was dropped to 2%.

## Concluding Remarks

The economic problems of excess capacity and overfishing have been the subject of considerable worldwide attention and concern in fisheries for decades, with capacity questions recently coming to the forefront. Limited consensus has, however, emerged about how one might effectively measure the extent of capacity utilization and use these estimates to guide policy formation and implementation to combat associated economic and biological pressures. In fact, very little information has been generated about the impacts of alternative definitions and estimating methods on capacity measures, especially at the boat level, that must be considered for implementation of vessel decommissioning schemes.

In this paper, we summarize the conceptual and theoretical basis for modeling

---

[31] The calculated critical value for vessel 2 was 41, which lies between the critical values for acceptance of the null hypothesis of equality, 26–94.

[32] Equality of SPF TE scores for all vessels could not, however, be rejected at the 2.5% level.

and measuring capacity output and utilization. We also suggest and empirically implement a range of possible capacity measures for the U.S. Northwest Atlantic scallop fishery. We estimate these measures using both the currently most common method for capacity utilization estimation in fisheries, data envelopment analysis (DEA), and its stochastic counterpart, stochastic production frontier analysis (SPF). These methods are efficiency based, which makes them comparable, but also raises questions about the role of technical efficiency in capacity measurement.

The empirical results indicate significant excess harvesting capacity for the vessels in our data set of about 25–30% overall (implying capacity reduction of 20–25% to reach full utilization), and more for the fleet if these estimates are extrapolated to boats that do (or could) fish in this fishery. However, this factor is not as large as some studies have suggested, at least in part due to the recognition of noise in the stochastic model (*e.g.*, Kirkley *et al.* 2001).

The results are also fairly consistent across specification, which seems largely attributable to comparing the capacity output measures to imputed technically efficient — rather than observed — output levels to reproduce customary and usual operating conditions. This is especially true for the models founded on the DEA notion of "unconstraining" variable inputs to impute the potential implied catch, rather than defining alternative input levels from which to evaluate the production relationship. The latter experiment is not well defined in the DEA context and exacerbates the influence of outliers. The results for each specification are also similar when not only days, but also stock levels and ultimately capital constraints (to mimic peak-to-peak approaches in a more structural framework), are unconstrained.

Greater discrepancies are evident if the measures are constructed on a vessel-specific basis. However, some consensus emerges about the "best" and "worst" boats (with little statistically significant variation in the mid-range), which could help to guide a decommissioning scheme targeting specific boats or types of boats to remove from the fishery in order to enhance the fishery's economic efficiency and viability.

Overall, computing a range of estimates seems desirable to evaluate the differences and similarities in the measures and assess the driving factors underlying the deviations that emerge. A combination of approaches and definitions is likely to be more effective for guiding policy implementation than reliance on one mechanism for capacity analysis.

## References

Aigner, D.J., C.A.K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6:21–37.

Battese, G.E., and T.J. Coelli. 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* 20:325–32.

Charnes, A., W. Cooper, A. Lewin, and L. Seiford (eds). 1994. *Data Envelopment Analysis: Theory. Methodology. and Application.* Boston, MA: Kluwer Academic Publishers.

Coelli. T. 1995. Recent Developments in Frontier Modelling and Efficiency Measurement. *Australian Journal of Agricultural Economics* 39(3):219–45.

Coelli, T., E. Grifell-Tatje, and S. Perelman. 2001. Capacity Utilization and Short Run Profit Efficiency. Working Paper, CEPA, School of Economics, University of New England, and CORE, Universiti Catholique de Louvain, September.

Coelli, T., S. Perelman, and E. Romano. 1999. Accounting for Environmental Influences in Stochastic Frontier Models: With Application to International Airlines. *Journal of Productivity Analysis* 11:251–73.

Coelli, T., D.S. Prasada Rao, and G.E. Battese. 1998. *An Introduction to Efficiency and Productivity Analysis*. Boston, MA: Kluwer Academic Publishers.

Cooper, W.W., L.M. Seiford, and K. Tone. 2000. *Data Envelopment Analysis*. Boston, MA: Kluwer Academic Publishers.

Dickie, L.M. 1955. Fluctuations in Abundance of the Giant Scallop, *Placopecten magellanicus* (Gmelin), in the Digby Area of the Bay of Fundy. *Journal of the Fisheries Research Board of Canada* 12:797–854.

Dupont, D.P., R.Q. Grafton, J.E. Kirkley, and D.E. Squires. 2002. Capacity Utilization Measures and Excess Capacity in Multi-product Privatized Fisheries. *Resource and Energy Economics* 24(3):193–210.

FAO. 1997. *The State of World Fisheries and Aquaculture. 1996*. Rome, Italy: Food and Agriculture Organization of the United Nations.

___. 1998. Assessing Excess Fishing Capacity at World-Wide Level. Rome, Italy: Food and Agriculture Organization of the United Nations.

Färe, R., S. Grosskopf, and E. Kokkelenberg. 1989. Measuring Plant Capacity. Utilization and Technical Change: A Nonparametric Approach. *International Economic Review* 30:655–66.

Färe, R., S. Grosskopf, and C.A.K. Lovell. 1994. *Production Frontiers*. Cambridge, United Kingdom: Cambridge University Press.

Felthoven, R.G. 2002. Effects of the American Fisheries Act on Capacity. Utilization and Technical Efficiency. National Marine Fisheries Service.

Felthoven, R.G., and C.J. Morrison Paul. 2004. Multi-Output, Non-Frontier Primal Measures of Capacity and Capacity Utilization. *American Journal of Agricultural Economics*, forthcoming.

Hilborn, R., and C.J. Walters. 1992. *Quantitative Fisheries Stock Assessment: Choice, Dynamics, and Uncertainty*. New York, NY: Chapman and Hall.

Holland, D., and S.T. Lee. 2002. Impacts of Noise and Specification on Estimates of Capacity Derived from Data Envelopment Analysis. *European Journal of Operations Research* 137(1):10–21.

Johansen, L. 1968. Production Functions and the Concept of Capacity. Recherches Recentes sur la Fonction de Production. Collection Economie Mathematique et Econometric 2. Belgium: Centre d'Etudes et de la Recherche Universitaire de Namur.

Kirkley, J.E., and D.E. Squires. 1998. *Measuring Capacity and Capacity Utilization in Fisheries*. Background paper prepared for FAO Technical Working Group on the Management of Fishing Capacity. April. *FAO Fisheries Report*.

Kirkley, J.E., R. Färe, S. Grosskopf, K.E. McConnell, D.E. Squires, and I.E. Strand. 2001. Assessing Capacity and Capacity Utilization in Fisheries when Data are Limited. *North American Journal of Fisheries Management* 21(3):482–97.

Kirkley, J., C.J. Morrison Paul, and D. Squires. 2002. Capacity and Capacity Utilization in Fishing Industries: Definition, Measurement, and a Comparison of Approaches. *Environmental and Resource Economics* 3:1–27.

Kirkley, J., D. Squires, and I. Strand. 1995. Technical Efficiency in Commercial Fisheries. *American Journal of Agricultural Economics* 77(4):686–97.

Klein, L.R. 1960. Some Theoretical Issues in the Measurement of Capacity. *Econometrica* 28:272–86.

Kumbhakar, S.C., and C.A.K. Lovell. 2000. *Stochastic Frontier Analysis*. New York, NY: Cambridge University Press.

Meeusen, W., and J. van den Broeck. 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review* 18:435–44.

Morrison, C.J. 1985. Primal and Dual Capacity Utilization: An Application to Productivity Measurement in the U.S. Automobile Industry. *Journal of Business and Economic Statistics* 3:312–24.

National Marine Fisheries Service (NMFS). 2001. Report of the Fishing Capacity Experts Meeting. Jon Sutinen, James Kirkley, Catherine Morrison Paul, Rolf Färe, Lee Anderson, and John Ward. May.

Northeast Fisheries Science Center. 1998. Status of Fishery Resources Off the Northeastern United States for 1998. NOAA Technical Memorandum NMFS-NE-115. September. Woods Hole, MA: NEFSC.

___. 1999. 1999 Scallop Fishery Management Plan SAFE Report (Stock Assessment and Fishery Evaluation). September. Woods Hole, MA: NEFSC.

Orea, L., A. Alvarez, and C.J. Morrison Paul. 2004. Modeling and Measuring Production Processes for a Multi-Species Fishery: Alternative Technical Efficiency Estimates for the Northern Spain Hake Fishery. *Natural Resources Modeling,* forthcoming.

Paloheimo, J.E., and L.M. Dickie. 1964. Abundance and Fishing Success. *Journal for the International Exploration of the Seas* 155:152–63.

Pennington, M. 1986. Some Statistical Techniques for Estimating Abundance Indices from Trawl Surveys. *Fisheries Bulletin* 3:519–25.

Reinhart, S., C.A.K. Lovell, and G. Thijssen. 2000. Environmental Efficiency with Multiple Environmentally Detrimental Variables: Estimated with SFD and DEA. *European Journal of Operational Research* 121:287–303.

Resti, A. 2000. Efficiency Measurement for Multi-product Industries: A Comparison of Classic and Recent Techniques Based on Simulated Data. *European Journal of Operational Research* 121:559–78.

Richards, L.J., and J.T. Schnute. 1986. An Experimental and Statistical Approach to the Question: Is CPUE an Index of Abundance. *Canadian Journal of Fisheries and Aquatic Science* 43:1214–27.

Westerheim, S.J., and R.P. Foucher. 1985. Relative Fishing Power for Canadian Trawlers Landing Pacific Cod (*Gadus macrocephalus*) and Important Shelf Cohabitants from Major Offshore Areas of Western Canada. 1960–1981. *Canadian Journal of Fisheries and Aquatic Science* 42:1614–26.

**Appendix Table A1**

Output (Catch) and Inputs, Total and Average Per Trip

| | Total | Boat 1 | Boat 2 | Boat 3 | Boat 4 | Boat 5 | Boat 6 | Boat 7 | Boat 8 | Boat 9 | Boat 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Total Catch ($Y_O$) | 5,296,925 | 689,076 | 101,656 | 510,933 | 562,906 | 543,373 | 573,026 | 679,699 | 569,056 | 548,530 | 518,670 |
| Average Catch ($Y_O$) | 9,117 | 10,938 | 6,777 | 7,299 | 10,424 | 8,110 | 8,954 | 11,520 | 9,178 | 8,707 | 8,104 |
| Total Days ($V_1$) | 8970 | 1021 | 148 | 994 | 906 | 1023 | 957 | 1035 | 976 | 970 | 940 |
| Average Days ($V_1$) | 15.44 | 16.21 | 9.87 | 14.20 | 16.78 | 15.27 | 14.95 | 17.54 | 15.74 | 15.40 | 14.69 |
| Max Days ($V_{1Max}$) | 26 | | | | | | | | | | |
| Average Crew ($V_2$) | 9.63 | 9.70 | 11.60 | 9.81 | 10.00 | 9.63 | 9.42 | 9.05 | 9.31 | 9.68 | 9.56 |
| Max Crew ($V_{2Max}$) | 15 | | | | | | | | | | |
| Average Stock ($S$) | 2.82 | 3.24 | 2.86 | 2.52 | 3.06 | 2.56 | 2.89 | 3.17 | 2.78 | 2.64 | 2.59 |
| Max $S$ ($S_{Max}$) | 6.85 | | | | | | | | | | |
| Target $S$ ($S_{Tar}$) | 9 | | | | | | | | | | |
| GRT ($K_1$) | 140.80 | 181 | 119 | 125 | 190 | 124 | 130 | 135 | 129 | 137 | 131 |
| HWP ($K_2$) | 539.62 | 620 | 500 | 520 | 620 | 520 | 520 | 520 | 520 | 520 | 520 |
| Dredge ($K_3$) | 14.48 | 15 | 13 | 13 | 15 | 13 | 15 | 15 | 15 | 15 | 15 |
| Length ($K_4$) | 86.30 | 90 | 80 | 85 | 90 | 85 | 85 | 87 | 85 | 87 | 85 |
| Number of Trips | 581 | 63 | 15 | 70 | 54 | 67 | 64 | 59 | 62 | 63 | 64 |
| Trips, Optdays (SPF) | 481 | 52 | 14 | 54 | 46 | 53 | 52 | 53 | 53 | 51 | 53 |
| Trips, Optdays (DEA) | 504 | | | | | | | | | | |

**Appendix Table A2**
Kruskal-Wallis Tests of Mean TE Value Equality

| Boats Tested | Degrees of Freedom | Calculated $\Pi^2$ TE-SPF | Calculated $\Pi^2$ TE-DEA | Chi-Squared 5.0% LOS | Chi-Squared 2.5% LOS |
|---|---|---|---|---|---|
| 1, 6, 7 | 2 | 5.992 | 6.549 | 5.991 | 7.378 |
| 1, 4, 6, 7 | 3 | 9.421 | 7.952 | 7.815 | 9.348 |
| 1, 4, 6 | 2 | 0.904 | 1.196 | 5.991 | 7.378 |
| 1, 4, 6, 9 | 3 | 2.144 | 4.541 | 7.815 | 9.348 |
| 1, 3, 4, 6, 9 | 4 | 2.314 | 7.411 | 9.488 | 11.143 |
| 1, 3, 4, 5, 6, 9 | 5 | 3.094 | 10.120 | 11.070 | 12.832 |
| 1, 3, 4, 5, 6, 8, 9 | 6 | 3.275 | 10.074 | 12.592 | 14.449 |
| 1, 3, 4, 5, 6, 8, 9, 10 | 7 | 5.772 | 16.471 | 14.067 | 16.013 |