The Australian Journal of
Agricultural and
Resource Economics

Journal of the Australian Agricultural and Resource Economics Society

The Australian Journal of Agricultural and Resource Economics, 54, pp. 343–360

Productive performance in fisheries: modeling, measurement, and management

Catherine J. Morrison Paul, Ronald G. Felthoven and Marcelo de O. Torres†

We overview the roles of production structure models in measuring fisheries' productive performance to provide policy-relevant guidance for fishery managers and analysts. In particular, we summarize the literature on the representation and estimation of production structure models to construct productive performance measures for fisheries, with a focus on parametric empirical applications and on the management implications of these kinds of measures.

Key words: fisheries, performance measurement, production economics.

1. Introduction

Seminal work on the economics of fishery management was published more than a half-century ago (Gordon 1954; Scott 1955), yet much of the fishery economics literature has continued to focus on problems associated with common-pool resources, as the implementation of rights-based fishery management around the world has slowly transitioned from theory to application. It is now well-known even by researchers and practitioners outside fisheries economics that when resource property rights are undefined yields are rivalrous, excess entry and input use are pervasive, and economic rents are dissipated. However, predicting the extent to which new management institutions or regulations aimed at addressing such problems may improve economic as well as biological performance, or evaluating whether past regulatory changes have improved or worsened performance, requires defining and measuring various aspects of fisheries' productive and economic performance (Weninger and Waters 2003; Kompas *et al*. 2004; Orea *et al*. 2005).

An issue of particular concern has been the extent of fishing capacity and capacity utilization in fisheries. One of the most striking symptoms of common-pool fisheries management around the world has been overinvestment in capital (vessels and equipment) and associated inefficient allocation of effort and increasing pressure on fish stocks. For over 20 years, the European Union has made structural adjustments to reduce overcapacity through the

† Catherine J. Morrison Paul (email: cjmpaul@primal.ucdavis.edu) is at the Department of Agricultural and Resource Economics and the Giannini Foundation, University of California, Davis, California, USA. Ronald G. Felthoven is at the U.S. National Marine Fisheries Service, Alaska Fisheries Science Center, Seattle, Washington, USA. Marcelo de O. Torres is at the Department of Economics, Catholic University of Brasília, Brasília, Brazil.

doi: 10.1111/j.1467-8489.2010.00496.x

multiannual guidance program, part of the Common Fisheries Policy.[1] The Food and Agricultural Organization has also called on nations to reduce fishing capacity for primary world species by 30 per cent to move toward sustainability of global fishery resources (FAO 1997, 1998). The US National Marine Fisheries Service (NMFS) has established guidelines to estimate and reduce excess capacity to eliminate overcapitalization in federally managed fisheries (NMFS 2001), and several of the Commonwealth fisheries in Australia have participated in the Fishing Concession Buyback in an effort to reduce fishing capacity.

Various methods have been proposed, including data envelopment analysis (DEA), stochastic production frontier (SPF), and econometric transformation function methods,[2] to measure the amount of overcapacity or the extent to which capacity has been reduced after programs aimed at capacity reduction have been implemented. However, no consensus has emerged on the 'best' way to model and measure capacity and capacity utilization for fisheries (Reinhart *et al.* 2000; Resti 2000; Espino *et al.* 2005; Lindebo 2005; Tingley and Pascoe 2005; Van Hoof and de Wilde 2005; Terry 2007).

Models used to measure the capacity of a fleet or vessel are often related to other measures of productive and economic performance such as technical efficiency (which implies using 'best practice' technology represented by a production frontier) or productivity growth (which implies shifts in the frontier).[3] These performance measures, which focus on the amount of output that may be produced from a given amount of inputs, also have input-specific counterparts that can be expressed as the output contributions or shadow values of particular factors underlying production processes, with performance and management connotations (Felthoven *et al.* 2009).

Constructing measures of capacity, efficiency or productivity for fishery managers requires modeling and estimating the production structure or technology. An initial issue that arises for such an effort is whether to adopt a primal or dual approach. Although dual models such as cost or profit functions provide a rich framework for representing relationships among inputs, outputs, and prices, their associated behavioural assumptions may be suspect if the incentives present in the particular application differ from those implied by the model.[4] For example, under a race for fish in common-pool fisheries, a skipper will likely seek to maximize catch subject to time constraints rather than to minimize the cost of landing a given amount of fish, violating the

[1] One of its objectives has been to maintain the appropriate size of the European Community's fleet. To assess capacity, only two fishing inputs (gross tonnage and engine kilowatt power) are used. This has led European researchers to look for new ways to assess capacity in fisheries (Santise and Nesci 2004; and Vestergaard 2005).

[2] For a comprehensive overview of these issues in the policy context see Pascoe *et al.* (2003a).

[3] Useful summaries of the conceptual basis and literature on efficiency, capacity, and productivity are contained in chapters 3–5 (respectively) of Grafton *et al.* 2006.

[4] Tests of concavity or convexity for cost and profit functions, respectively, can provide insight into whether the specifications, including the behavioural assumptions, are well-posed.

assumptions of a cost function model (Felthoven and Morrison Paul 2004b). Empirical implementation of such cost models may also be subject to other practical limitations, as input price and cost data are usually lacking for fisheries. However, as data are often available on prices as well as quantities of fish sold, and fishermen might affect products sold because of fishing area or processing choices, revenue function models are sometimes used to assess these issues for fisheries (Kirkley and Strand 1988).[5]

Largely because of such conceptual and input data limitations (Grafton *et al*. 2000; Herrero and Pascoe 2003), primal models that represent the technological relationships between inputs and outputs without behavioural assumptions have increasingly been used to represent production structure and performance for fisheries applications. Various performance measures may be constructed from primal production structure models. For example, a distance or ray production function (Löthgren 1997) can provide measures of technical (in)efficiency by estimating the deviation of each observation from the estimated production frontier (the most output producible given observed input use). These models can then be used to construct measures of capacity output by characterizing some inputs as 'fixed' (the capacity base) and representing the potential shift in the production frontier if that base was used 'optimally' by expanding variable inputs.[6] Productivity measures can be constructed by instead examining shifts in the frontier from, say, the passage of time (disembodied technical change) or the purchase of specific technology/equipment (embodied technical change; Kirkley *et al*. 2004a). These measures of deviations from or shifts in the production frontier may be thought of as overall productive performance measures, versus individual factor measures capturing the contributions of specific factors as marginal products or shadow values with respect to particular production structure arguments.

A key issue that arises for the empirical implementation of such production structure/performance models is what estimation method to use, such as mathematical programming (typically DEA),[7] parametric econometric (typically SPF), or growth accounting methods. Parametric methods require choosing a specific *type* of function (e.g., distance, transformation, or production functions) for estimation, a choice that at least partly depends on whether one is using frontier analysis (allowing for deviations from the frontier) or more traditional 'average' least squares to estimate the production frontier (Felthoven and Morrison Paul 2004b). For econometric estimation,

[5] Revenue functions have been specified both for choices of species (Kirkley and Strand 1988; Squires and Kirkley 1991) and products processed from the fish (Asche and Hannesson 2002; Morrison Paul *et al*. 2009).

[6] This assumption is valid over the study period of most applied fishery production models in the literature, but some vessel characteristics used to represent the capacity base do change in the state and federal databases and such changes should be accommodated in the model.

[7] Stochastic DEA techniques have been developed (Sengupta 1990; Cooper 1998; Huang and Li 2001), but programming methods are inherently deterministic.

specification tests regarding the functional form are often undertaken (e.g., what flexible functional form to use or how many interaction terms are appropriate; Felthoven and Morrison Paul 2004b), and for frontier analysis, additional specification tests may be conducted to properly specify the distribution of inefficiency terms (e.g., gamma or half-normal distributions; Kumbhakar and Lovell 2000).

Another implementation issue is specifying the arguments of the function – the inputs and outputs (netputs) as well as other factors that influence the relationships among netputs (and shift or twist the production frontier). Early papers that motivated the field of fisheries economics (Schaefer 1954; Scott 1955) conveyed the idea of input use in terms of an 'effort' variable. Following this convention, many studies in the fisheries production literature have used a composite effort variable such as days fished (Kirkley and Strand 1988), but production theory suggests that labour, capital, and energy inputs be more explicitly represented.[8]

By relaxing the common assumptions of a single composite input (and separability of this input from the outputs), one can more fully consider the interactions among the inputs used for production. In particular, capital heterogeneity may by captured by including vessel-specific measures of engine power and size, or even fishing strategies such as the number or duration of hauls in a given time period (Felthoven *et al*. 2009).[9] Accounting for heterogeneity in inputs also allows one to distinguish inputs that are constrained (e.g., vessel characteristics), which in turn allows one to estimate the substitutability between constrained and unconstrained inputs and thus the degree to which input controls are likely to be effective (Campbell 1991; Dupont 1991) or to affect the efficiency of fishery participants (Kompas *et al*. 2004).[10]

For outputs, most fisheries involve multiple species even if there is only one 'target' species, so the production structure specification should accommodate multiple outputs. Incorporating multiple species also allows analysts to examine the degree of jointness or separability among species, which in turn impacts the way fisheries should be managed (e.g. as a single species or as a joint complex fishery). For example, it has implications for discards and bycatch as well as the nature of the catch accounting system (or observer programs) utilized to estimate the total amount of fish extracted from the ecosystem (Squires and Kirkley 1991; Squires *et al*. 1998).

[8] As highlighted by one of the referees, there may be measurement problems associated with labour as an input, and endogeneity issues can arise in revenue function specifications if crew wage is a function of revenue or catch (as in a share – or lay – system; McConnell and Price 2004).

[9] Furthermore, in cases where economic input or cost measures are desirable but elusive, physical effort measures may be a good proxy (Pascoe *et al*. 2003a,b).

[10] For example, when input controls are not likely to be viable, a fixed cap on total catch and individual transferable quotas (ITQs) will be a preferred means of managing a fishery (Squires and Kirkley 1991; Squires *et al*. 1998).

Technology and technical change embodied in inputs may also be important to represent if possible (such as equipment on board as well as vessel characteristics), as they may determine what fishing choices may be made by the skipper. Explicitly recognizing other nondiscretionary production factors in the estimating model, such as fish stocks, environmental factors (weather), and regulatory constraints, may also be more crucial for fisheries than for other industries. For example, how available fish stocks or proxies of stock abundance are incorporated can lead to marked differences in results and can bias parameter estimates (Hilborn and Walters 1992; Andersen 2005; Zhang and Smith 2007).[11]

Although many of these issues of netput definition have been addressed to some extent in the literature, other issues that may be important for economic performance analyses and their relevance to fisheries management have not received much attention. One of these involves spatial considerations such as movements of fish stocks or regulatory limitations on fishing location (e.g., area closures) or practices (e.g., bottom-trawling prohibitions). Another involves constraints on vessels' adaptability to changing environments because of biological limitations (e.g., seasonal variations in stock availability or quality) or technological limitations (e.g., lacking the gear to fish for certain species). Such issues in turn raise questions about the dimensions of the data and its aggregation (over time, by vessel, across space) for empirical implementation.

2. Modeling production processes and performance for fisheries

Modeling economic performance for fisheries requires representing the production structure (and in the case of dual models, incorporating optimization behaviour) based on the outcomes that define performance such as production and growth (or dual cost or revenue levels). In primal models that represent the technological structure but not economic behaviour, performance is defined by the amount of output (catch) possible to 'produce', given the inputs used and other 'environmental' factors affecting production (e.g., biological stocks and weather).

For multiple outputs (species), the production structure can generally be characterized by the production technology set $\mathbf{T}(\mathbf{y}, \mathbf{x}, \mathbf{r})$ that represents the transformation of production factors or inputs $\mathbf{x}$ and environmental factors[12] $\mathbf{r}$ into outputs (catch) $\mathbf{y}$ and contains all technically feasible input and output

[11] When such factors cannot be adequately characterized because of the absence or spatial/temporal aggregation of data, one can still construct measures of productive performance, but the sources of the changes in performance will be confounded and results must be interpreted in this context.

[12] Common environmental factors relevant to fishery production models include stock abundance, fish size and age distribution, spatial and temporal distribution, fishing strategies such as haul size and tow duration, management constraints, and weather and climatic factors (Weninger 2001; Felthoven *et al.* 2009).

bundles. **T** can be used to define the producible output set $\mathrm{Y}(\mathbf{x}, \mathbf{r}) = \{\mathbf{y}: (\mathbf{x}, \mathbf{y}, \mathbf{r}) \in \mathrm{T}\}$ and the input requirement set $\mathrm{V}(\mathbf{y}, \mathbf{r}) = \{\mathbf{x}: (\mathbf{x}, \mathbf{y}, \mathbf{r}) \in \mathrm{T}\}$ as equivalent representations of the technology set, in that $\mathbf{x} \in \mathrm{V}(\mathbf{y}, \mathbf{r}) \iff \mathbf{y} \in \mathrm{Y}(\mathbf{x}, \mathbf{r})$. The boundaries of these two sets can loosely be thought of as the more common production possibilities frontier and input isoquant, respectively.

Various primal functional representations of **T** may be specified to facilitate multiple-output analyses, each of which have different advantages and disadvantages for modeling and measuring economic production and performance (Felthoven and Morrison Paul 2004b; Orea *et al*. 2005). For example, under particular conditions on the technology (Hall 1973),[13] the production technology set **T** can be expressed in terms of the transformation function $0 = \mathrm{F}(\mathbf{y}, \mathbf{x}, \mathbf{r})$ by normalizing one output, which becomes the left-hand-side variable with all other arguments on the right-hand-side: $y_1 = g(\mathbf{y}_{-1}, \mathbf{x}, \mathbf{r})$ (where $\mathbf{y}_{-1}$ is the vector of all output except y_1).[14] However, when one variable is chosen as numeraire, performance estimates represent changes in that variable (y_1) given the levels of other outputs and inputs, which may be problematic if, say, the production of one output cannot be raised without increasing other output(s) (suggesting that the technical condition of 'free disposability' of outputs is not a valid assumption). In addition, parameter estimates will not be invariant to the choice of numeraire because the sum of squared residuals will be minimized with respect to different outputs (unlike distance function applications; Coelli and Perelman 2000).

If only one (aggregate) output is specified, $g(\bullet)$ reduces to a standard production function with additional limitations; outputs and inputs are essentially treated as separable[15] (as well as outputs being aggregable) so input mix changes do not affect the slope of the production possibility curve (Orea *et al.* 2005). A multiple-equation production function model may also be developed from the transformation function, although such models require inputs to be allocated among outputs, which is not possible if production is joint (Orea *et al*. 2005).

Another functional representation of the technology set **T** often used for fishery applications is the distance function (Shephard 1953), which can be expressed in terms of either outputs or inputs.[16] An output distance function, written as $\mathrm{D_O}(\mathbf{y}, \mathbf{x}, \mathbf{r})$, is defined as the maximal proportional expansion of the output vector given output composition, the levels of **x** and **r**, and the production technology **T**. This function thus represents the distance from the

---

[13] Specifically, if $\mathrm{F}(\mathbf{y}, \mathbf{x}, \mathbf{r})$ is continuously differentiable and has nonzero first derivatives with respect to one of its arguments (say the first output, y_1), the transformation function $\mathbf{F}(\mathbf{x}, \mathbf{y}, \mathbf{r})$ can be specified to represent the production technology $\mathbf{T}(\mathbf{x}, \mathbf{y}, \mathbf{r})$ via the implicit function theorem as $y_1 = g(\mathbf{y}_{-1}, \mathbf{x}, \mathbf{r})$.

[14] See Felthoven and Morrison Paul (2004b) for an application of such a function to estimation of capacity and capacity utilization in fisheries.

[15] See Brown *et al.* (1979).

[16] See Orea *et al.* (2005) for an application to measurement of efficiency in fisheries.

frontier (technical inefficiency) as well as the frontier itself (through its dependence on the production possibility set); if no inefficiency exists, $D_O(\mathbf{y}, \mathbf{x}, \mathbf{r}) = 1$ is equivalent to $F(\mathbf{y}, \mathbf{x}, \mathbf{r}) = 0$.

However, issues also arise for empirical implementation of $D_O(\mathbf{y}, \mathbf{x}, \mathbf{r})$; in particular, economic performance measures based on this function reflect expansion of one output given observed output composition (rather than given other output levels, as for the transformation function). That is, formally expressing the model as an econometrically estimable equation results in the left-hand-side (numeraire) variable appearing in the denominator of right-hand-side variables. That is, for econometric application, the theoretical requirement of linear homogeneity in outputs results in $D_O(\mathbf{y}, \mathbf{x}, \mathbf{r})/y_1 = D_O(\mathbf{y^*}, \mathbf{x}, \mathbf{r})$ (where $\mathbf{y^*}$ is the vector of all outputs normalized by output y_1).

Further, implementing the model requires the use of a logarithmic functional form (such as a Cobb-Douglas or translog), which does not accommodate zero output or input values. More specifically, to write the function with an observable left-hand-side variable and to separate the distance from the frontier as a one-sided error term, the function is written as $\ln y_1 = h(\ln \mathbf{y^*}, \ln \mathbf{x}, \ln \mathbf{r}) - \ln D_O = h(\ln \mathbf{y^*}, \ln \mathbf{x}, \ln \mathbf{r}) - u$, so the function is expressed in terms of output ratios and logarithms.[17]

Such a model is often used to characterize the extent of technical efficiency,[18] where estimates of $h(\bullet)$ represent the technology and of $\ln D_O$ represent inefficiency.[19] That is, efficiency is measured by how close observed production comes to ‘potential’ output (catch), given output composition.[20] Various methods can be used to estimate such a model, but all involve ‘enveloping’ the function to represent the most production possible from a given amount of inputs; for example, deterministic DEA programming methods construct a piecewise linear frontier around all the observations, and econometric SPF methods estimate a differentiable (smooth) frontier allowing for white noise. Once the production frontier is estimated, the implied technically efficiency output, y^{TE}, is imputed by a radial expansion (a line in two-dimensional space) from the origin to the frontier through the data point. This ‘potential’ output is then compared to the observed output, y^O, to obtain the efficiency ratio or ‘score’ $y^O/y^{TE} \leq 1$ or $y^{TE}/y^O \geq 1$ indicating the deviation from the frontier.

[17] This makes it natural to assume a logarithmic functional form such as a translog for empirical application of this model; assuming such a flexible form minimizes the assumptions imposed on the data and allows for second-order production characteristics such as technical change biases, but cannot well accommodate zero input or output values.

[18] See, for example, Orea *et al*. (2005), Kirkley *et al*. (2002), and Dupont *et al*. (2002).

[19] Although the distance function by construction recognizes $\ln D_O$ as the distance from the frontier, one may also posit a one-sided error term for other functions such as production or transformation functions.

[20] Adjustment of other outputs, recognizing the extent to which they are joined by parametric estimates may, however, be accommodated empirically as in Felthoven and Morrison Paul (2004b).

The latter measure is interpreted as indicating the proportion by which output would increase if inefficiency was eliminated (the observed output was scaled up to the frontier). For fisheries, it may be problematic to interpret such an output gap as 'inefficiency', as lower reported catch levels may be attributable to unobserved but 'customary and usual' operating conditions outside the skipper's control (such as fluctuating fish stocks or weather, and crew or vessel problems) rather than revealing a short-fall from 'potential' catch. However, such measures have been used both as indicators of efficient resource utilization (Kompas *et al.* 2004; Tingley *et al.* 2005) and as a step toward representing capacity output (Dupont *et al.* 2002; Kirkley *et al.* 2002).

Measuring capacity output (y^C) for fisheries involves expanding the notion of potential output or catch to reflect the amount that could be produced if the capacity base (for fisheries typically the fixed vessel stock) was fully utilized by increasing variable inputs, rather than how much could be caught given observed (fixed and variable) input levels (y^{TE}).[21] Capacity utilization (CU) is then measured by comparing capacity output 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 or as y^C/y^O to represent the proportion by which output could expand to full utilization given the capacity base (Kirkley *et al.* 2002).

The primary problem for constructing such capacity and CU measures is defining the notion of potential, optimum or maximum output underlying y^C. Given our (and the literature's) focus on primal models for fisheries, it is natural to think of capacity as the 'most output possible', given the existing capacity (fixed input) base. Conceptually, this can be defined as the technically efficient output plus the output change from shifting the production frontier by relaxing binding constraints on variable input use (such as regulations on days at sea or trip limits), or as a technological maximum like the point where the marginal products of variable inputs are zero. In particular, Johansen's (1968) definition of capacity as '…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' is often relied on for fishery capacity analysis (Dupont *et al.* 2002; Grafton *et al.* 2006).

To represent this concept, one must distinguish variable (**v**) and fixed (capital, **k**) inputs in the **x** vector and determine how much catch would be possible if variable inputs were unconstrained. One often-used method is to assume that, because fishing days are constrained by fishery regulations, 'days' is the variable input constraint to be relaxed to infer capacity output; the resulting measure is often called 'technological-economic' if it is bounded by observed

[21] Capacity output is often just called 'capacity' in the fisheries literature, although this is potentially confusing because the capacity base, which is determined by the level of fixed inputs, is also sometimes called capacity, as in the definition of 'excess capacity' (Kirkley *et al.* 2002, 2004a,b).

catch and thus is implicitly consistent with economic motivations (Kirkley *et al*. 2001). This typically empirically involves applying linear programming DEA methods without days included as a constraining input, or econometric SPF methods without days included as a regressor (Kirkley *et al*. 2002). Other methods include using historic data on the greatest number of days fished by a vessel during the year (Felthoven *et al*. 2004), inferring the point where the marginal product of days would be zero (Kirkley *et al*. 2004a,b), or considering a reasonable percentage increase in days (say, 25 or 50 per cent) and estimating how moving to that number of fishing days would affect catch (Felthoven and Morrison Paul 2004b).[22]

However, other variables might also be thought to potentially change in an unconstrained state, such as fish stock and crew, which can result in a range of possible scenarios to define capacity output (NMFS 2001; Kirkley *et al*. 2002, 2004a,b). Essentially, it is arbitrary to hypothesize how regulatory changes would relax the restrictions under which participants in the fishery operate and to represent the resulting hypothetical increases in effort. In particular, it might well not be 'feasible' (or consistent with customary and usual operating practices that would still prevail in an unconstrained fishery) to increase all variable inputs to highest levels seen in the data – and in fact fishing could become *less* intensive if regulatory constraints were relaxed (Felthoven 2002).

In addition to issues about defining y^C, defining an appropriate comparison output to compute CU measures for fishery applications raises questions – particularly if frontier methods are used to measure y^C that implicitly embody y^{TE}. Some economists have suggested that one should compute what they refer to as an 'unbiased' estimate of CU, y^{TE}/y^C, to accommodate this problem (Fare *et al*. 1989; Holland and Lee 2002), and empirical estimates have shown that doing so reduces discrepancies from estimating DEA versus SPF frontier models or distance versus transformation function models (Kirkley *et al*. 2002, 2004a,b; Felthoven and Morrison Paul 2004b). However, this also suggests that frontier methods may not be required or even desirable for estimating capacity output, as technically 'efficient' output may not be practically feasible because of the many unobservable production factors in fisheries that may preclude a vessel from achieving the most 'efficient' catch levels.

As a result, in applied policy settings, it can be somewhat difficult or tenuous to utilize results from frontier models (and primal orientations in particular) to suggest particular capacity-reduction goals. Not only is the degree of measured overcapacity relatively dependent on model assumptions and specifications, some policy makers may question, for example, the production-based notion of keeping only the most efficient vessels operating in a fishery, as considerations over small-vessel participants and community protection

[22] In a dual framework, Pascoe (2007) uses a unique approach of first estimating the efficient and full utilization levels of output in a DEA model and then estimating a long-run cost function coinciding with full efficiency and utilization.

measures can carry significant weight in fishery management decisions. Using efficiency scores or rankings for allocation decisions is subject to similar issues. This conflict is unfortunate, however, as production analysis is so amenable to management decisions; e.g., restructuring programs often need a common unit of effort beyond just vessel numbers or characteristics (such as size or engine power), and production analysis can be based on either an input (vessel) or output (catch) orientation depending on the focus of the management issue.

Measuring productivity, in addition to capacity and efficiency, can provide important insights about fishery performance – but again faces issues about appropriately representing the production structure and its changes. Unlike efficiency or capacity measures, which infer 'potential' output by characterizing 'best practice' production or relaxing input constraints, productivity measures reflect shifts in the production frontier. In econometric models, such shifts are modeled as the output contributions of 'technical change' – often defined simply as the passage of time but also potentially by observable technological innovations.[23]

That is, measuring productivity in such a context involves including variables representing technical change as **r** vector components in the function representing the production structure, such as the transformation function $y_1 = g(\mathbf{y}_{-1}, \mathbf{x}, \mathbf{r})$ or distance function $\ln y_1 = h(\ln \mathbf{y}^*, \ln \mathbf{x}, \ln \mathbf{r}) - u$. The contributions to output growth of these variables are then estimated, holding constant other productive factors included as arguments of the function. This essentially decomposes the factors contributing to the growth of y_1 (the target catch), with a focus on shifts in the frontier over time (t) or from identifiable technical changes.

More specifically, formally constructing a productivity growth equation involves including time (t) as a component of the **r** vector in a model of the production structure and taking the total derivative of the function with respect to t. In the context of a transformation function, this would result in:

$$\frac{dy_1}{dt} = \sum_{m-1} \frac{\partial g}{\partial y_{-1,m}} \frac{dy_{-1,m}}{dt} + \sum_{i} \frac{\partial g}{\partial x_i} \frac{dx_i}{dt} + \sum_{j} \frac{\partial g}{\partial r_j} \frac{dr_j}{dt} \tag{1}$$

where m denotes the components of $\mathbf{y}_{-1}$, i the components of **x,** and j the components of **r**. This equation is then transformed into percentages (so all derivatives are in logarithmic form), and the derivative with respect to t, $\partial g/\partial t$, is put on the left-hand-side of the expression and dy_1/dt on the right-hand-side (Felthoven and Morrison Paul 2004a). In this context, productivity growth – the change in y_1 attributable to the passage of time controlling for (or distin-

[23] Programming models such as DEA and Malmquist indexes can also be used to distinguish technical inefficiency (the distance of an observation from a piece-wise linear productivity frontier) and total factor productivity (a shift in the frontier), as in Kerstens *et al.* (2005), Hoff (2006), and Squires *et al.* (2008).

guishing the independent contributions of) all other arguments of the function – is expressed as the total observed change in y_1 minus a weighted (by marginal products) sum of the observed changes in all other arguments of the transformation function.

Measuring the marginal products or shadow values $\partial g/\partial y_{-1,m}$, $\partial g/\partial x_i$, and $\partial g/\partial r_j$ to substitute in the productivity growth expression may be accomplished by econometric/parametric estimation of the production technology (Felthoven *et al.* 2009). Alternatively, assumptions may be used to approximate them by observed data; for example, optimal (profit-maximizing) input demand may be assumed to justify approximating the marginal (revenue) products of inputs by their market prices, resulting in 'growth accounting' productivity growth measures (Squires 1992; Jin *et al.* 2002). However, such assumptions may not be appropriate for quasi-fixed inputs (the marginal product and market price will not be equivalent except when the fixed input is at its equilibrium level) and cannot be used for productive factors that do not have a market price (such as weather and biological stock which may be crucial productivity determinants for fisheries).

Measuring productivity growth for fisheries can help to identify changing technological or economic pressures on the biological stock over time. However, the individual catch contributions or shadow values of arguments of the function other than *t* are also of interest. For example, if variables representing specific types of equipment are included in the **r** vector, their catch contributions (marginal products or shadow values, $\partial g/\partial r_j$) may be identified from parametric estimation of the function representing the production structure (Kirkley *et al.* 2004a,b); such measures capture increased pressure on the biological stock from technological innovation. The shadow values of environmental variables such as weather can similarly provide indicators of changing pressures on the stock, as can the shadow values of adaptations in production strategies resulting from regulatory changes (Felthoven *et al.* 2009).[24] Further, estimated shadow values of bycatch species could potentially indicate the productive constraints from imposing area closures to protect such species.

3. Management implications of performance measurement for fisheries

Although several countries, including Australia, New Zealand, and the United States, are increasingly relying on measures of productive or economic performance to improve fisheries management, such measures are still underutilized by fisheries managers relative to their biological counterparts. While considering measures of stock abundance or ecosystem health is clearly fundamental to providing responsible stewardship of fishery resources, the kinds

[24] Note also that the effects on such measured productive contributions (marginal products or shadow values) of a particular factor from changes in other arguments of the function – or cross-effects – can be measured if the estimated function is approximated by a flexible functional form.

of economic measures discussed in this article also can and should be relied on to help maximize fisheries' net benefits.[25] This can be accomplished in several ways.

At the most basic level, measures of capacity, efficiency, and productivity can be computed for a fleet or fishery to generate a time series of economic indicators to evaluate the status quo management regime (Greenville *et al.* 2006). This information can also be integrated with biological information to generate a more complete picture of a fishery's performance status. For example, Zhang *et al.* (2009) construct ecosystem indexes of sustainability, biodiversity, habitat quality, and economic performance and develop methods to link the three, to provide a synthesized view of fishery performance.

Such economic time series can also be used to examine changes in net benefits or productive performance from changes in fishery management strategies by constructing simulations.

More specifically, in overcapitalized fisheries, one can estimate the fishing capacity of vessels in the current fleet and predict the likely reduction in overcapacity that could be motivated by a buyback program (Kirkley and Walden 2003) or an ITQ-based system to facilitate consolidation (Weninger and Waters 2003). The criteria for identifying the most viable vessels to stay in the fleet could be the most technically efficient, the least cost or the most profitable vessels (the choice of which may depend on data availability).[26] However, in such instances, congestion externalities can be a factor affecting the efficiency of current vessels, which could lead to downward bias in estimates of efficiency or productivity in the ex-post fishery. With fewer participants, vessels will be less inclined to spill over into less productive fishing grounds, generating potential increases in average productivity for the fleet, thus affecting the number of vessels constituting the most efficient sized fleet.

Other productive performance measures can also help to inform fishery managers. For example, sectoral allocations of a fishery to different fleets or gear groups that may operate at differing levels of efficiency or profitability are often carried out by fishery managers. Such allocations are typically enacted to preserve the historic participation of particular groups, so potential gains from trade between more and less efficient operators are not realized. It would be possible in these situations, however, to assess the costs of relative performance by simulating the fleet that would emerge if fishing activity or quota was transferred across sectors of different efficiency or productivity levels and constructing economic performance measures for this resulting fleet.

[25] In Australia, explicit mention of economic performance as one of the goals in fisheries management is contained in Fisheries Management Act 1991 Act No. 162 of 1991; in New Zealand in their Statement of Intent 2009–2014; in the US in the United States Executive Order 12866 (Federal Register 1993).

[26] In reality, horizontal or vertical integration and cash flow may also be important determinants of survival in a transition to an ITQ system.

Similar analyses could also be conducted to assess the effects of a change from managing fishery resources in a common-pool structure to a rationalized, rights-based fishery (Squires 1994; Grafton *et al*. 2000; Herrmann 2000; Sigler and Lunsford 2001; Felthoven 2002). Two impacts should be distinguished in such a case (Brandt 2007). The first is the change in economic performance from changes in the composition of the fleet (such as consolidation), as fleet efficiency should increase as more profitable vessels outbid other vessels for quota. The second is the change in performance from the different environment in which vessels now operate, as vessels under ITQs or other rights-based regimes will likely be less concerned about racing for their share of the catch and more concerned with efficiency and productivity. Innovations in production that were not feasible in the original system may therefore become feasible, leading to increased product quality or recovery rates (Felthoven 2002; PCC 2007).

Further, competing uses among marine mammals, fish stocks, and industrialized fisheries often (and increasingly over time) lead to fishing area closures to protect areas of particular concern. Such marine-protected areas may be implemented to preserve essential fisheries habitat, preserve the food supply for marine mammals or protect the sea floor from structurally damaging bottom trawls. To achieve these benefits, costs are imposed on vessels by restricting fishing to areas that may be less productive or farther from shore. In this case, discrete location choice models can be used to predict the redistribution of effort to outlying areas, and production models based on location-specific estimates of past performance can be used to infer the likely economic consequences of site closures.

The spatial dimension of productive performance requires further development in future research. In particular, analyses of fishery production/performance are typically carried out with unbalanced panel data, recognizing the time series (yearly, seasonal, weekly/monthly or trip) and cross-section (fleet or vessel) dimensions. However, the panel nature of this data raises implementation and interpretation issues. For example, estimation using trip-level data defines performance measures in terms of the catch produced per-trip for each vessel, although for many policy concerns annual vessel activity over the entire fleet may be relevant (Kirkley *et al*. 2004a,b). Such issues are exacerbated when one adds a spatial dimension to fishery models (Smith 2005). For example, important localized conditions may not be captured by data for survey region or management area, and records for fish landings often pertain to the proportion of catch or effort in large 'zones' that are defined differently by management agencies with different jurisdictions (e.g., state or federal; Smith and Wilen 2003). Issues about how econometrically to represent the spatial dimension then arise for adding this dimension to the production and/or econometric model, say, through fixed effects or spatial autocorrelation models.

Other issues to better address in future research include the relationship between productive performance and biological or technological constraints.

For example, some species may be caught less frequently in certain seasons because of migratory, spawning or other biological patterns, and some products (such as roe) may also be only feasible to produce seasonally (Morrison Paul *et al*. 2009). Technological constraints may also be binding determinants of production feasibility or choices if, for example, some vessels do not have the fishing or processing equipment on board to catch/produce some species/products. Such constraints that limit production possibilities could be taken into account by, say, double hurdle or latent class models.

In short, a range of productive performance measures can help to inform fishery managers about the status of a current fishery or the predicted or actual impacts of various management changes. We should note, however, that along with such measures, it is important to provide fishery managers with information about the level of *precision* of estimated economic performance changes. Confidence intervals can be most readily constructed for measures from econometric models, but bootstrapping techniques (Efron and Tibrishani 1993) can also be applied to mathematical programming models to infer the reliability of estimates (albeit with a slightly different statistical interpretation).

4. Concluding remarks

In this article, we have summarized much of the literature on productive performance estimation for fisheries, including capacity, efficiency, and productivity measurement. We have focused on empirical (particularly econometric) performance analysis, the advantages and disadvantages of different modeling and empirical choices, and the use of such analyses for guiding management decisions. We hope that this overview will help researchers, practitioners, and managers to understand the thrust of applied production modeling of fishery economic performance, its contributions and limitations, and its potential to guide fishery management.

References

Andersen, J.L. (2005). The inclusion of stocks in multi-species fisheries: the case of Danish seiners, *Marine Resource Economics* 20, 163–184.

Asche, F. and Hannesson, R. (2002). Allocation of fish between markets and product forms, *Marine Resource Economics* 17, 225–238.

Brandt, S. (2007). Evaluating tradable property rights for natural resources: the role of strategic entry and exit, *Journal of Economic Behavior & Organization* 63(1), 158–176.

Brown, R.S., Caves, D.W. and Christensen, L.R. (1979). Modeling the structure of cost and production for multiproduct firms, *Southern Economic Journal* 46, 256–273.

Campbell, H.F. (1991). Estimating the elasticity of substitution between restricted and unrestricted inputs in a regulated fishery: a probit approach, *Journal of Environmental Economics and Management* 20(3), 262–274.

Coelli, T. and Perelman, S. (2000). Efficiency measurement, multiple-output technologies and distance functions: with application to European railways. CREPP (Research Center on Public and Population Economics) Working Paper 9605, University of Liege.

Cooper, W. (1998). Chance constrained programming formulations for stochastic characterizations of efficiency and dominance in DEA, *Journal of Productivity Analysis* 9(1), 53–79.

Dupont, D.P. (1991). Testing for input substitution in a regulated fishery, *American Journal of Agricultural Economics* 73(1), 155–163.

Dupont, D.P., Grafton, R.Q., Kirkley, J. and Squires, D. (2002). Capacity utilization measures and excess capacity in multi-product privatized fisheries, *Resource and Energy Economics* 24(3), 193–210.

Efron, B. and Tibrishani, R. (1993). *An Introduction to the Bootstrap*. Chapman and Hall, New York, NY.

Espino, D., del Hoyo, J. and Sharp, B. (2005). Capacity and capacity utilization of the ''Voracera'' fleet in the Strait of Gibraltar, *Marine Resource Economics* 20(4), 367–384.

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

FAO (1998). *Assessing Excess Fishing Capacity at World-Wide Level*. Food and Agriculture Organization of the United Nations, Rome.

Fare, R., Grosskopf, S. and Kokkelenberg, E.C. (1989). Measuring plant capacity, utilization and technical change: a nonparametric approach, *International Economic Review* 30, 655–666.

Felthoven, R.G. (2002). Effects of the American Fisheries Act on the harvesting capacity, capacity utilization, and technical efficiency of pollock catcher-processors, *Marine Resource Economics* 17, 181–205.

Felthoven, R.G. and Morrison Paul, C.J. (2004a). Directions for productivity measurement in fisheries, *Marine Policy* 28, 161–169.

Felthoven, R.G. and Morrison Paul, C.J. (2004b). Multi-output, non-frontier primal measures of capacity and capacity utilization, *American Journal of Agricultural Economics* 86(3), 619–633.

Felthoven, R., Hiatt, T. and Terry, J. (2004). Measuring fishing capacity and utilization with commonly available data: an application to Alaskan fisheries, *Marine Fisheries Review* 64(4), 29–39.

Felthoven, R., Morrison Paul, C. and Torres, M. (2009). Measuring productivity change and its components for fisheries: the case of the Alaskan pollock fishery, 1994–2002, *Natural Resource Modeling* 22(1), 105–136.

Gordon, H.S. (1954). The economic theory of a common-property resource: the fishery, *Journal of Political Economy* 62(2), 124–142.

Grafton, R.Q., Squires, D. and Fox, K.J. (2000). Private property and economic efficiency: a study of a common-pool resource, *Journal of Law and Economics* 43(2), 679–713.

Grafton, R.A., Kirkley, J., Kompas, T. and Squires, D. (2006). *Economics for Fisheries Management*. Ashgate Press, Burlington, VT.

Greenville, J., Hartmann, J. and Macaulay, T. (2006). Technical efficiency in input-controlled fisheries: the NSW Ocean Prawn Trawl Fishery, *Marine Resource Economics* 21, 159–179.

Hall, R. (1973). The specification of technology with several kinds of output, *Journal of Political Economy* 81(4), 878–892.

Herrero, I. and Pascoe, S. (2003). Value versus volume in the catch of the Spanish South-Atlantic trawl fishery, *Journal of Agricultural Economics* 54(2), 325–341.

Herrmann, M. (2000). Individual vessel quota price-induced effects for Canadian Pacific halibut: before and after Alaska IFQs, *Canadian Journal of Agricultural Economics* 48, 195–210.

Hilborn, R. and Walters, C.J. (1992). *Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty*. Chapman and Hall, International Thomson Publishing, Norwell, MA.

Hoff, A. (2006). Bootstrapping Malmquist indices for Danish seiners in the North Sea and Skagerrak, *Journal of Applied Statistics* 33(9), 891–907.

Holland, D. and Lee, S.T. (2002). Impacts of random noise and specification on estimates of capacity derived from data envelopment analysis, *European Journal of Operational Research* 137, 10–21.

van Hoof, L. and de Wilde, J.W. (2005). Capacity assessment of the Dutch beam-trawler fleet using data envelopment analysis (DEA), *Marine Resource Economics* 20(4), 327–345.

Huang, Z. and Li, S. (2001). Stochastic DEA models with different types of input-output disturbances, *Journal of Productivity Analysis* 15(2), 95–113.

Jin, D., Thunberg, E., Kit-Powell, H. and Blake, K. (2002). Total factor productivity change in the New England groundfish fishery, 1964–1993, *Journal of Environmental Economics and Management* 44(3), 540–555.

Johansen, L. (1968). Recherches récentes sur la fonction de production [Production functions and the concept of capacity]. Centre d'Etudes et de Recherches Universitaires de Namur.

Kerstens, K., Squires, D. and Vestergaard, N. (2005). Methodological reflections on the short-run Johansen industry model in relation to capacity management, *Marine Resource Economics* 20(4), 425–443.

Kirkley, J. and Strand, I. (1988). The technology and management of multi-species fisheries, *Applied Economics* 20, 1279–1292.

Kirkley, J. and Walden, J. (2003). A limited economic assessment of the Northeast groundfish fishery buyout program, *Land Economics* 79(3), 426–439.

Kirkley, J.E., Fare, R., Grosskopf, S., McConnell, D.E., Squires, D.E. and Strand, I.E. (2001). Assessing capacity and capacity utilization in fisheries when data are limited, *North American Journal of Fisheries Management* 21(3), 482–497.

Kirkley, J., Morrison Paul, C.J. and Squires, D. (2002). Capacity and capacity utilization in common-pool resource industries, *Environmental and Resource Economics* 22, 71–97.

Kirkley, J.E., Cunningham, S., Catanzano, J. and Morrison Paul, C.J. (2004a). Embodied and disembodied technical progress in fisheries: an analysis of the Sete trawl fishery 1985–1999, *Environmental and Resource Economics* 29(2), 191–217.

Kirkley, J., Morrison Paul, C.J. and Squires, D. (2004b). Deterministic and stochastic capacity estimation for fishery capacity reduction, *Marine Resource Economics* 19, 271–294.

Kompas, T., Che, T.N. and Grafton, R.Q. (2004). Technical efficiency effects of input controls: evidence from Australia's banana prawn fishery, *Applied Economics* 36(15), 1631–1641.

Kumbhakar, S. and Lovell, C.A.K. (2000). *Stochastic Frontier Analysis*. Cambridge University Press, Cambridge, UK.

Lindebo, E. (2005). Multi-national industry capacity in the North Sea flatfish fishery, *Marine Resource Economics* 20(4), 385–406.

Löthgren, M. (1997). Generalized stochastic frontier production models, *Economics Letters* 57, 255–259.

McConnell, K. and Price, M. (2004). The Lay system in commercial fisheries: origin and implications, *Journal of Environmental Economics and Management* 51, 295–307.

Morrison Paul, C.J., Torres, M. and Felthoven, R. (2009). Fishing revenue, productivity, and product choice in the Alaskan pollock fishery, *Environmental and Resource Economics* 44, 457–474.

National Marine Fisheries Service (NMFS) (2001). Report of the fishing capacity experts meeting, with Jon Sutinen, James Kirkley, Catherine Morrison Paul, Rolf Färe, Lee Anderson, and John Ward, May.

Office of the Federal Register (1993). Executive order 12866: regulatory planning and review, Federal Register 58(190). Washington DC, USA.

Orea, L., Alvarez, A. and Morrison Paul, C.J. (2005). Modeling and measuring production processes for a multi-species fishery: alternative technical efficiency estimates for the Northern Spain hake fishery, *Natural Resources Modeling* 18, 183–214.

Pascoe, S. (2007). Estimation of cost functions in a data poor environment: the case of capacity estimation in fisheries, *Applied Economics* 39, 2643–2654.

Pascoe, S., Kirkley, J.E., Greboval, D. and Morrison Paul, C.J. (2003a). *Measuring and Assessing Capacity in Fisheries*. FAO Fisheries Technical Paper No. 433/2, FAO, Rome.

Pascoe, S., Hassaszahed, P., Anderson, J. and Korsbrekke, K. (2003b). Economic versus physical input measures in the analysis of technical efficiency in fisheries, *Applied Economics* 35(15), 1699–1710.

PCC (Pollock Conservation Cooperative) (2007). Pollock Conservation Cooperative and High Seas Catchers' Cooperative Final Report to the North Pacific Fishery Management Council, Seattle, WA. Available from URL: http://www.atsea.org/doc/PCCHSCCAnnRept 11-30-09r1.pdf.

Reinhart, S., Lovell, C.A.K. and Thijssen, G. (2000). Environmental efficiency with multiple environmentally detrimental variables: estimated with SFD and DEA, *European Journal of Operational Research* 121, 287–03.

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, 559–578.

Santise, A. and Nesci, F.S. (2004). Ineffectiveness of the common policy for fishing capacity reduction, *Mediterranean Journal of Economics, Agriculture and Environment* 3(2), 50–57.

Schaefer, M. (1954). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries, *Bulletin of the Inter-American Tropical Tuna Commission* 1, 26–56.

Scott, A. (1955). The fishery: the objectives of sole ownership, *Journal of Political Economy* 63(2), 116–124.

Sengupta, J. (1990). Transformations in stochastic DEA models, *Journal of Econometrics* 46(1–2), 109–123.

Shephard, R. (1953). *Cost and Production Functions*. Princeton University Press, Princeton, NJ.

Sigler, M. and Lunsford, C. (2001). Effects of individual quotas on catching efficiency and spawning potential in the Alaska sablefish fishery, *Canadian Journal of Fisheries and Aquatic Sciences* 58(7), 1300–1312.

Smith, M.D. (2005). State dependence and heterogeneity in fishing location choice, *Journal of Environmental Economics and Management* 50(2), 319–340.

Smith, M.D. and Wilen, J.E. (2003). Economic impacts of marine reserves: the importance of spatial behavior, *Journal of Environmental Economics and Management* 46(2), 183–206.

Squires, D. (1992). Productivity measurement in common property resource industries: an application to the Pacific coast trawl fishery, *Rand Journal of Economics* 23, 221–236.

Squires, D. (1994). Sources of growth in marine fishing industries, *Marine Policy* 18(1), 5–18.

Squires, D. and Kirkley, J. (1991). Production quota in multiproduct Pacific fisheries, *Journal of Environmental Economics and Management* 21, 109–126.

Squires, D., Campbell, H., Cunningham, S., Dewees, C., Grafton, R.Q., Herrick, S., Kirkley, J., Pascoe, S., Salvanes, K., Shallard, B., Turris, B. and Vestergaard, N. (1998). Individual transferable quotas in multispecies fisheries, *Marine Policy* 22(2), 135–159.

Squires, D., Reid, C. and Jeon, Y. (2008). Productivity growth in natural resource industries and the environment: an application to the Korean tuna purse seine fleet in the Pacific Ocean, *International Economic Journal* 22(1), 81–93.

Terry, J. (2007). An assessment of the use of capacity analysis in U.S. federal fishery management, *Marine Resource Economics* 22(1), 99–103.

Tingley, D. and Pascoe, S. (2005). Eliminating excess capacity: implications for the Scottish fishing industry, *Marine Resource Economics* 20(4), 407–424.

Tingley, D., Pascoe, S. and Coglan, L. (2005). Factors affecting technical efficiency in fisheries: stochastic production frontier versus data envelopment analysis approaches, *Fisheries Research* 73(3), 363–376.

Vestergaard, N. (2005). Fishing capacity in Europe: special issue introduction, *Marine Resource Economics* 20, 323–326.

Weninger, Q. (2001). An analysis of the efficient production frontier in the fishery: implications for enhanced fisheries management, *Applied Economics* 33, 71–79.
Weninger, Q. and Waters, J. (2003). Economic benefits of management reform in the northern Gulf of Mexico reef fish fishery, *Journal of Environmental Economics and Management* 46(2), 207–230.
Zhang, J. and Smith, M. (2007). Bias correction in an empirical fishery model: a two-stage approach. Working Paper, Nicholas School of the Environment and Earth Sciences, Duke University.
Zhang, C.I., Kim, S., Gunderson, D., Marasco, R., Lee, J.B., Park, H.W. and Lee, J.H. (2009). An ecosystem-based fisheries assessment approach for Korean fisheries, *Fisheries Research* 100(1), 26–41.