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Productivity growth, catchability, stock assessments, and optimum renewable resource use

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ABSTRACT

Productivity growth substantially impacts rent-maximizing resource stocks, and can lead to an economic optimum that has overfished stocks: BMEY < BMSY. Bioeconomic models can give biased results and policy advice when not accounting for time-varying catchability—notably due to productivity growth—and density-dependent catchability, and not distinguishing between fishery-dependent and fishery-independent data and implications for catchability, modeling, and applicability of results. Productivity growth, as a component of time-varying catchability, also impacts stock assessments. CPUE standardization and productivity measurement both face an identification issue in disentangling changes in resource stocks from changes in productivity as well as endogenous regressors for which there are potential identification strategies. An empirical example illustrates BMEY < BMSY.

1. Introduction

Growth in productivity or fishing power impacts the optimum exploitation of renewable resources such as marine capture fisheries.[1] This paper examines several of these key impacts upon bioeconomic models, population assessments, and the consequent policy recommendations.

First, the paper considers the effects of accounting for productivity growth in normative bioeconomic models. The bioeconomics literature, recently reviewed by [1–4], has largely overlooked the growing body of economic literature on the economics of productivity growth, reviewed by [5] in this volume. The bioeconomics literature recommends dynamic maximum economic yield (MEY) and biomass (or numbers of animals), denoted by B, of the resource stock (BMEY) corresponding to BMEY > BMSY (maximum sustainable yield resource stock), because a larger biomass lowers search and harvest costs that in turn raise economic rent [6–8]. In contrast, after incorporating productivity growth into bioeconomic models, BMEY < BMSY, because productivity growth lowers search and harvest costs on an on-going basis, and when coupled with discounting, there are weaker incentives to lower costs by keeping fish in the water [3].

The bioeconomics literature reaches additional conclusions that may not hold when incorporating productivity growth. The perceived crisis in global fisheries [7,9] is likely misstated in terms of economic rent, effective effort, and natural capital when productivity growth is accounted for in bioeconomic modeling [3]. Recommended optimum fleet sizes, nominal effort or physical capital levels, resource stock targets, and policy instruments simply do not match the more productive technology and its continual growth that are ongoing but are unaccounted for in current dynamic models. Rebuilding strategies [8] do not correspond to BMEY and impose unnecessary costs when accounting for productivity growth. The presence of productivity growth increases the risk of extinction, and more generally biodiversity loss, greater than considered by [1] and others. The bionomic (open-access) equilibrium of Gordon [10] may only exist, if at all, at levels much lower than currently held.

Second, the paper discusses how accounting for productivity growth and its measurement are closely related to issues that arise with catchability in population assessments and that also bear upon bioeconomic models.[2] The population assessment,

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[1] Productivity is an economic measure of total catch per unit of a single input (partial productivity) or per unit of all inputs (total factor productivity). Productivity is often called fishing power in the fisheries literature. Productivity (fishing power) growth is due to many factors, the most important of which is technological change.

[2] Catchability has several definitions [11]. One is the parameter that relates an index of relative abundance to population size (absolute abundance). Another is the proportionality parameter between fishing effort and fishing mortality or the portion of the stock captured by one unit of effort. The earliest known theoretically rigorous economics paper on time-varying and density-dependent catchability is [12]. Ekerhovd and Gordon [13] also raise the identification issue when using resource stock to evaluate catch-effort (or by extension productivity) relationships, and propose a specific identification strategy for VPA models. This paper builds upon both papers, as well as [11] and [3].

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bioeconomic, and fisheries productivity literatures grapple with, or should grapple with, catchability that is potentially time-varying and density-dependent and with the implications from using fishery-dependent and fishery-independent data.[3] Most importantly, stock assessments aim to remove the effect of productivity growth from stock estimates and economists want to remove the effect of stock changes from productivity growth. Both require an identification strategy to disentangle the two sources of change, often using the same fishery-dependent data. Productivity theory also provides a number of insights for standardization of catch and effort data.

Third, there is not an explicit, theoretically consistent mechanism to incorporate productivity growth into population assessments, and this paper discusses some possible approaches. Through the empirical example, the paper shows how to specify the catchability coefficient to account for growth in productivity or fishing power consistent with productivity theory. In this vein, catch per unit effort or CPUE, which is typically a partial rather than total factor productivity measure, may not accurately measure relative stock abundance and/or density, since not all economic inputs, and in many instances productivity growth, that affect fishing mortality are captured.

This paper illustrates the impact of productivity growth, measured by an economic index number, upon MEY and BMEY for the US and Canada Pacific coast albacore (*Thunnus alalunga*) troll fishery. It employs a very simple bioeconomic model that accounts for productivity growth. It eschews a spatial bioeconomic model with density-dependent fish movement between spatially linked distinct populations or substocks, because supporting empirical biological evidence is absent for many fish species, and especially for northern albacore, which make ontogenetic migrations [14].[4]

Section 2 discusses the relationships between productivity measurement and catchability, population assessments, bioeconomic models, and the use of fishery-dependent and -independent data. Section 3 summarizes growth accounting and productivity, the Malmquist productivity measure, and bioeconomic models. Section 4 incorporates productivity growth into the Golden Rule of renewable resource economics. Section 5 provides empirical results and discusses policy implications. Section 6 concludes.

2. Catchability and fishery-dependent and -independent data

2.1. Issues in catchability

Several questions arise for productivity growth measures and bioeconomic models and their relationship to catchability and population assessments and the use of fishery-dependent and -independent data.[5] First, catchability, of which productivity is a part, may be density-dependent (elaborated upon below), so that bioeconomic models and population assessments may not fully and accurately track the entire population [11,12].[6]

Second, both productivity measures and stock assessments may use all or part of the same fishery-dependent data, potentially requiring an identification strategy to disentangle changes in resources stocks from changes in productivity. Third, productivity measures may use estimates of stock size from assessments that incorporate time-varying catchability. This can confound the productivity measures, since productivity measures are only one of several potential sources of time-varying catchability. Again, an identification strategy is required. Fourth, productivity measures can employ absolute resource stock measures or relative changes in stocks, where the latter are generally considered more reliable and the former are not always available (e.g., from yield-per-recruit analysis [15]). Fifth, catchability may be effort-dependent, in which catchability varies with the level or scale of effort and the crowding externality [12]. However, other than noting knowledge spillovers that depend upon the level of investment in physical capital, this fifth topic is left for future discussion.

Before proceeding to consider the first three questions in greater depth, note that CPUE, a widely used measure of relative stock abundance and/or of local density, is an average product of effort and a partial productivity measure, since only a single input is used, such as a measure of fishing time (days, sets). In contrast, total factor productivity (TFP) is measured using all inputs, since TFP is measured as a residual after accounting for changes in all inputs, including resource stocks [16]. CPUE, when a partial productivity measure, may not accurately measure relative stock abundance, since not all inputs that affect fishing mortality are captured.[7]

2.2. Density-dependent catchability

Productivity measures, bioeconomic models, and stock assessments are all potentially subject to density-dependent catchability of harvesting vessels. A stock is not evenly distributed and changes spatially and temporally as its abundance changes [11,12,18,19]. In addition, fisher search is non-random or there can be gear saturation or density-dependent gear avoidance behavior, all of which can affect catchability in fisheries and surveys. Fleet spatial expansion can also affect density-dependent catchability.

Density-dependent catchability has implications for use of fishery-dependent and fishery-independent data. Stock assessment from a restricted part of a stock's range requires the stock to decrease in the same proportion across the entire range in which it is fished, a linear relationship [11,18,19]. For CPUE to represent abundance, averaging catch rates for any time period over only areas fished requires assumptions about what catch rates would have been in areas that had not yet or were no longer fished [11,20]. Ignoring unfished areas and averaging only over areas fished (i.e., using fishery-dependent data) essentially assumes fleets behaved the same in both fished and unfished areas, and leads catchability and productivity measures to potentially exhibit "hyperstability" or "hyperdepletion." Density-dependent

[3] The most common source of fishery-dependent data is catch and effort information from commercial or recreational fishers. Surveys and life history studies provide some of the most important sources of fishery-independent data. Population assessments have long recognized these issues as is discussed herein.

[4] Source-sink larval or density-dependent fish movements between patches or meta-populations are not biologically supported spatial processes with albacore (and most other small and large pelagic species and some demersal species) [14]. Albacore broadcast spawn, and age 2–5 albacore migrate along the North Pacific Transition Zone.

[5] The discussion follows the bulk of the population dynamics literature and is couched in terms of surplus production models, in which catchability may be represented by a single coefficient. However, Eric Thunberg (personal communication) notes that in age-based or cohort models, catchability is represented as a vector. If selectivity is dome shaped, density-dependent growth may influence the number of ages that remain susceptible to the gear.

[6] An anonymous referee noted that the traditional view of density-dependent catchability posits that even if data are available for the whole population, the observed trend in the index does not track that of the population due to a nonlinear relationship between them. This is a different but related, problem to only having data for a portion of the population.

[7] Excluding the resource stock leaves a TFP residual that reflects changes in both productivity and the resource stock [16]. CPUE as a measure of abundance faces considerable problems [17]. Further, CPUE used as a measure of abundance in productivity and standardization studies creates an identification issue in regression models, such as general additive models or generalized linear models, to analyze and explain variations in stock abundance or to standardize effort. The identification issue arises when catch and/or effort are on both sides of the equation, leading to simultaneity bias, and when the regressor effort is a behavioral variable (a choice variable decided upon by fishers) and endogenous, potentially leading to biased and inconsistent parameter estimates

catchability typically increases as abundance declines, thereby causing "hyperstable" CPUE, in which CPUE remains high despite decreases in abundance [12,18,19].

Density-dependent catchability is also an issue for bioeconomic models, which are almost always estimated using fishery-dependent data. Bioeconomic models are typically meant to apply to the entire fishery, whether fished or unfished, which means that they can suffer from the same uncertainties as that of stock assessments. BMEY might be derived from only a portion of the potentially fished area.

Density-dependent catchability from using fishery-dependent data is less troublesome to measures of productivity growth or technological change, because these are positive measures based on "what is," i.e., actual fleet behavior and performance in actual areas fished, rather than the entire resource stock range. When these productivity measures are used in bioeconomic models, the issue of density-dependent catchability does not arise unless the productivity measure pertains to only some of the relevant vessels in a non-representative way or fleet expansion to unfished areas is anticipated.

2.3. Time-varying catchability

In contrast to the bioeconomics literature, the population dynamics literature accounts for time-varying catchability [11].[8,9] Not accounting for time-varying catchability would otherwise lead to biased estimates of stock size and stock productivity. Anthropogenic, environmental, biological, and management processes may drive changes in catchability over time. Time-varying catchability can be found in both fishery-dependent and -independent data sources, although it is generally believed more prevalent in fishery-dependent data (survey vessels are more consistent in gear, technology, areas surveyed, etc. than commercial vessels).

Several approaches standardize effort or CPUE data series for time-varying catchability or allow catchability to vary over time [11,17,21]. Standardization aims to ensure that the catchability coefficient can be assumed constant, i.e., control effects other than those caused by changes in stock size, notably changes in productivity, density or effort dependence, species targeting, environment, and dynamics of the fleet or population (especially factors leading to density-dependent catchability). Effort or CPUE is adjusted for known changes in efficiency, or effort in other gears is converted to a standard gear in which catchability is not thought to have changed (a process called standardization). The various methods for standardization of catch and effort data define the efficiency of a fishing vessel as its fishing power relative to that of a standard (and perhaps hypothetical) fishing vessel, most commonly by the ratio of the two CPUEs [21].[10]

Productivity theory provides insights for standardization. Standardization employing a standard production unit (e.g., gear group or vessel) can be viewed in economics as a multilateral productivity index or a frontier function estimated using panel data with deterministic or stochastic half-sided error terms. Standardization as an a-theoretical approach assumes a single aggregate technology across multiple fleets/gears, which allows aggregating through fixed proportions over time, although consistent aggregation has rigorous economic requirements [22]. Standardization also implies Hick's neutral technical change with a static-reference technology base including fleet and time period.[11] Furthermore, constant and/or time-invariant returns to scale is typically assumed, which does not allow for differences over time in the structure of production and does not satisfy all the desirable properties of economic index numbers. Assuming a particular functional form for the aggregator functions of catch and effort that give catch and effort indices may be prone to potentially restrictive properties, and may be subject to intransitive bilateral comparisons and failure of Fisher's factor reversal test (also an issue for bioeconomic models).[12] Finally, CPUE standardization can only correct for measured factors that affect catchability and requires available data for each factor [11].

As an alternative to standardization to account for time-varying catchability, catchability can be explicitly modeled as a function of time [11,23], including explicit technical progress [12]. This approach captures all sources of time-varying productivity, so that changes in productivity are conflated with abundance (and perhaps environment), and confronts the same problem as TFP measurement, that of disentangling TFP and stock changes with a time trend (or related variable). Simply put, stock assessments aim to remove the effect of productivity growth from stock estimates and economists want to remove the effect of stock changes from productivity growth. Both approaches require an identification strategy to disentangle the two sources of change, often using the same fishery-dependent data.

Productivity and economic index number theory has implications for catchability explicitly modeled as a function of time. As with standardization, such an approach typically only captures Hick's neutral disembodied technical change.[13] Interactions between time and explanatory variables allow for biased technical change that changes the ratio of inputs over time, but complicate use of time to measure abundance changes [21]. This approach does not typically capture embodied technical change,[14,15] or time-varying changes in technical efficiency,[16] or nonlinear relationships between effort and technical change such as congestion (crowding) spillovers [12] and knowledge spillovers.[17] A linear time trend captures only a constant rate of technological change

[8] The population dynamics literature does not explicitly account for productivity growth (fishing power), which is one component of time-varying catchability. The fishing power literature is not based upon a consistent and comprehensive theory of production, and is largely an a-theoretical, reduced-form, statistical analysis.

[9] An alternative, not discussed here, is time-varying selectivity.

[10] Parameter estimates used in regression analyses of standardization could be biased and inconsistent due to endogenous explanatory variables (unless found otherwise through Hausman tests), such as effort (days/sets/trips) or catch of other species. Endogenous regressors require an identification strategy and instrumental variable estimation. Standardization may overlook heteroscedasticity and serial correlation and cluster-specific heteroscedasticity and serial correlation with panel data.

[11] The question of static reference technology basis arises as whether to compare the technology of periods t and $t+1$ using period t technology or period $t+1$ technology or the geometric mean of both, which is what the Malmquist index does. Hick's neutral means that the ratios of inputs remain constant with technological change, so that for example, physical capital (e.g., boat, gear) is not favored over labor (crew). Biased technological change occurs when one input is relatively favored over another. Fisher's factor reversal test states that the product of the effort index and price index equals total cost.

[12] Comparisons, such as standardization, should be transitive. For example, fleet A has say more fishing power than fleet C, and fleet B has less fishing power relationship to fleet C, then the fishing power of A should exceed B.

[13] Disembodied technical change refers to technical change that is not embodied in an economic input, notably the capital stock or is not investment-specific, i.e., it is independent of physical capital accumulation. Disembodied technical change often refers to learning how to work with new technology that leads to changes in fishing and post-capture handling practices.

[14] Unless indicators such as new use of a technology (e.g., GPS) are included as regressors, but then run into the problem of varying rates of adoption and diffusion throughout the fleet plus knowledge spillovers.

[15] Embodied technical change is incorporated into an input (typically the physical capital stock) through net investment in the input. Examples include new designs in the hull, propeller, and gear, changing materials (e.g., steel versus wood hull, monofilament nylon net instead of natural materials), Medina panel, information technology-embodied electronics and gear, all largely meant to improve productivity (fishing power).

[16] Technical efficiency refers to the maximum catch per unit of effort (input) given a technology.

[17] Consider nominal effort in time t, E_t^{α}. Then $\alpha<1$ gives congestion (crowding) (regardless of whether there is technological change) and $\alpha>1$ gives knowledge spillovers when there is technological progress. $\alpha=1$ is expected with externalities since linear homogeneity is required for the effort aggregator function for a consistent index.

and a quadratic allows a variable rate. Time specified in blocks or steps is related to the general index of technical change [24]. Catchability can also be modeled as a function of density or an environmental variable, although this approach excludes productivity growth, essentially assuming it is static over time. Finally, catchability can be allowed to change over time using state space models. Random walks have been used, and perform better with slower changing populations. All these standardization approaches are a-theoretical vis-à-vis the economic theory of technological change and more generally, productivity growth and properties of economic index numbers, and make a number of implicit assumptions that can affect results.

2.4. Productivity measurement using fishery-dependent and -independent data

TFP measures calculated using fishery-dependent data may be confounded when using stock abundance measures from stock assessments also estimated from fishery-dependent data, an identification issue. Stock assessments accounting for time-varying catchability already, in some fashion, account for growth in TFP (and other time-varying factors). The TFP residual then measures, at least in part, what has already been accounted for using the same data.

There are a number of identification strategies. One identification strategy revolves around using fishery-independent data. Stock estimates from fishery-independent data may not confound TFP measures, since stock estimates are exogenous to the fleet. Surveys providing fishery-independent data that use a standardized design and cover the full potential range of the stock will also be least susceptible to time-varying catchability [11]. Nonetheless, stock estimates using only fishery-independent data may not reflect the abundance and availability actually encountered by vessels and thereby give biased or less precise productivity measures.

Another identification strategy employs a two-step method. TFP growth is first estimated using stocks estimated employing fishery-independent data. This estimate, then employs the productivity growth measure in additional stock estimates, and productivity growth is then re-estimated using all data, etc., in an iterative approach.[18] An additional identification strategy uses integrated stock assessment models to measure TFP growth. These assessments use both fishery independent and dependent data. They also utilize considerable information exogenous to the productivity measure, including cohort, gender, age-length or size-length, and recruitment [25]. Structure on growth and recruitment functions also assists the identification strategy. Yet another identification strategy uses the structure of fishery-dependent data as an identification strategy in VPA models [13].[19] Still another identification strategy occurs if the stock assessment uses fishery-dependent data from additional fleets or areas that the TFP measure does not.

2.5. Incorporating productivity growth into stock assessments and related bioeconomic models

As noted, there is not an explicit, theoretically consistent mechanism to incorporate productivity growth into population assessments, and this paper provides some insights. Notably, when the effort measure excludes the physical capital stock in general and investment in this stock in particular (e.g., echo sounders), time-varying catchability does not have a mechanism to incorporate technology that enters through net investment in physical capital (i.e., embodied technical change), although if the time trend captures the productivity residual, it does so implicitly [26]. Depending upon how effort is measured, the economically optimal combination of multiple inputs (allocative efficiency) may not be considered. Similarly, without a best-practice harvesting frontier, technical efficiency is excluded. That is, unless the fishery harvest function relating catch to effort and stock distinguishes production units (countries, ports, fleets, individual vessels) with higher catch per unit of effort for a given harvesting technology (technical efficiency) compared to fishers with lower catch per unit of effort, then there is not any way to allow for deviations in catch per unit of effort to vary by production units. Instead, all production units are implicitly specified to have the same technical efficiency. Knowledge and congestion spillovers that create a nonlinear catch-effort relationship are excluded. [20] That is, one vessel's investment in say fish-finding electronics makes new knowledge about technological options and how to use them available to other vessels, which in turn increases the effectiveness of this investment and the adoption of new technology. This knowledge spillover effect is external to the production process, i.e., is an externality. In short, the whole is greater than the sum of the parts.

In principle, the catchability coefficient can be decomposed into one part systematically accounting for productivity growth theoretically consistent with productivity and economic growth theories and calculated using fishery-dependent data and a residual catchability part accounting for other sources of time variability, such as environmental changes. Many of these other components cannot be estimated without auxiliary information, and changes in selectivity (age- or length-based patterns in catchability) may also be conflated with changes in overall catchability [11]. When abundance indices are calculated with fishery-independent data, the possibility arises for a constant catchability.

Bioeconomic models may also be extensions of population assessments rather than independently specified and estimated. Such bioeconomic models based upon time-varying catchability using standard stock assessment approaches only account for disembodied technical change, and exclude: investment in physical capital that incorporates embodied technology; changes in technical efficiency; input substitution; and knowledge and congestion spillovers, all economically endogenous sources of change. Such bioeconomic models estimated with time-varying catchability and fishery-dependent data face potential density-dependent catchability issues, and if estimated with fishery independent data may not accurately account for changes in technology or technical efficiency. Bioeconomic models estimated with fishing time (e.g., days/sets) as a measure of effort assume time rather than physical capital as the limiting input (Leontief separability) and preclude investment in physical capital, embodied technical change, input substitution, and knowledge spillovers as economically endogenous sources of change.

3. Growth accounting and Malmqvist–Törnqvist productivity measures

In this study, the productivity growth residual measured by

[18] Mark Maunder (personal communication) suggested this possibility. This "two-step" approach differs from integrated analysis in which the parameters of the population dynamics model and those related to catch-effort standardization are estimated simultaneously by optimizing an objective function for all sources of data available to the stock assessment model [25].

[19] Ekerhovd and Gordon [13] (p. 382) observe, "…generated VPA stock estimates must be correlated with the error term in a regression equation of catch on stock because current stock is a function of current catch. To achieve consistent estimates of the econometric equation it is necessary to instrument out current catch in the VPA stock estimate." Page 383 gives the specific instruments.

[20] The overall state of technology in the competitive fishery sector can be determined in part by knowledge spillovers from investment in physical capital (e.g., engines, electronics) embodied with new exogenous technology. Each unit of net investment not only increases both the individual vessel's and aggregate stock of knowledge-embodied physical capital, but also increases the level of technology and productivity for all vessels in the fishery.

growth accounting is first developed and is subsequently estimated. Let Y_t denote catch in time t, X_{1t} denote variable inputs, X_{2t} denote physical capital stock, B_t denote natural resource stock, dots over a variable denote proportional rates of growth, M_{2t} is the cost share of physical capital, ψ_t denote rate of embodied technical change, and λ denote constant rate of Hick's neutral, exogenous, disembodied technical change. Under constant returns to scale in effort, Hicks neutral exogenous technical change, full capacity utilization for X_{2t}, full technical efficiency for reasons other than embodiment of technology in capital, input allocative efficiency in the aggregator functions for X_{1t} and X_{2t}, and no changes in output quality) [16,26]: $\dot{Y} = (1 - M_{2t})\dot{X}_{1t} + M_{2t}\dot{X}_{2t} + \dot{B}_t + M_{2t}\psi_t + \lambda$. Rearranging gives the growth rate in the Solow TFP [27] residual: $\dot{\phi} = \dot{Y}_t - (1 - M_{2t})\dot{X}_{1t} - M_{2t}\dot{X}_{2t} - \dot{B}_t = M_{2t}\psi_t + \lambda$. The rate of embodied technological change, ψ_t, is then equal to $\left[\dot{\phi} - \lambda_t\right]/M_{2t}$. B_t may not be uniformly distributed, such as with schooling fish. B_t can then be weighted, giving B_t^{α} [12] and $\alpha\dot{B}_t$ replaces $\dot{B}_t$ in the growth accounting equation. For both the sole owner [16] and non-uniformly distributed B_t, there is no longer a one-to-one relationship between B_t and Y_t.

The Malmqvist TFP index between periods t and $t-1$ can be approximated by the ratio of a Törnqvist output index to a Törnqvist input index under constant returns to scale in both periods [28].[21] [22] This provides a "Hicks–Moorsteen" TFP measure, giving the ratio of growth in total output to growth in total input. To employ economic index numbers, competitive input and output markets is assumed, which is a plausible assumption here.

The Törnqvist index for effort in time t, E_t, is as follows:

$$ln\left[\frac{E_t}{E_{t-1}}\right] = ln\left[\frac{X_{1t}}{X_{1t-1}}\right]\left[\frac{M_{1t} + M_{1t-1}}{2}\right] + ln\left[\frac{X_{2t}}{X_{2t-1}}\right]\left[\frac{M_{2t} + M_{2t-1}}{2}\right], \tag{1}$$

where $M_{it} = \frac{c_{it}}{\sum_{i=1}^{2} c_{it}}$ is the share or proportion of c_{it} or the cost input X_{it} in total costs ($\sum_{i=1}^{2} c_{it}$), the cost of input X_{it} is $c_{it} = r_{it}X_{it}$, and r_{it} is the price of X_{it}, $i=1$, 2. It is equivalently:[23]

$$E_{t,t-1} = \prod_{i=1}^{2}\left[\frac{X_{it}}{X_{it-1}}\right]^{0.5(M_{it}+M_{it-1})}. \tag{2}$$

The Malmqvist–Törnqvist bilateral TFP index with a single output is as follows:

$$lnTFP_t - lnTFP_{t-1} = \tag{3}$$

$$\left[lnY_t - lnY_{t-1}\right] - \sum_{i=1}^{2} 0.5(M_{it} + M_{it-1})\left[lnX_{it} - lnX_{it-1}\right] - \left[lnB_t - lnB_{t-1}\right],$$

or equivalently is:

$$\frac{TFP_t}{TFP_{t-1}} = \frac{Y_t}{Y_{t-1}}\Bigg/\left[\prod_{i=1}^{2}\left[\frac{X_{it}}{X_{it-1}}\right]^{0.5(M_{it}+M_{it-1})} * \frac{B_t}{B_{t-1}}\right]. \tag{4}$$

A single input is used with a fixed proportions technology. This index imposes both technical and allocative efficiency and constant returns to scale. Technical efficiency implies evaluating temporal changes in the production frontier without deviations due to "catching up" or "falling behind".

The TFP index for the albacore fishery case study is comprised of US vessels over 1981–1989 and both U.S. and Canadian vessels over 1990–2009. The geometric mean of the Törnqvist TFP indices is employed for the U.S. and Canada to obtain an aggregate Malmqvist–Törnqvist TFP index for the years 1990–2009:

$$TFP_{t,t-1} = \left[\frac{TFP_t^{US}}{TFP_{t-1}^{US}} \cdot \frac{TFP_t^{CAN}}{TFP_{t-1}^{CAN}}\right]^{0.5}. \tag{5}$$

The albacore stock is assessed without time-varying catchability using an integrated analysis (Stock Synthesis 3) and using both fishery-dependent and independent data [30].[24] Statistical (Hausman) tests indicated that the stock estimate is exogenous to effort, and this identification should hold for the deterministic productivity indices [3].[25] This study uses the S4 (base case) and S2 (third case) time-invariant catchability coefficients from the 2014 assessment [30] (WCPFC 2014).

4. Productivity growth and the golden rule of renewable resource economics

The golden rule or fundamental equation of renewable resources with disembodied and embodied technical change, full capital utilization, and accounting for technical inefficiency in the yield frontier and allocative efficiency with effort is as follows:[26]

$$\frac{\partial F}{\partial B_t} + \frac{\alpha c F(B_t)}{\left(PqB^{\alpha}e^{(\lambda+M_2\beta_1\psi)t-\mu(t,Z)} - c\right)B_t} + \frac{c\left(\lambda + M_2\beta_1\psi - \partial\mu(t,Z)/\partial t\right)}{\left(PqB_t{}^{\alpha}e^{(\lambda+M_2\beta_1\psi)t-\mu(t,Z)} - c\right)} = \delta, \tag{6}$$

where the biological (logistic) growth function is $dB_t/dt = F(B_t) - Y_t$, P denotes constant ex-vessel price, δ denotes the discount rate, $-\partial\mu(t, Z)/\partial t$ denotes a nonpositive, half-sided error term capturing time-varying deviations from the best-practice frontier or technical inefficiency and allows for "catching up" and "falling" behind the frontier over time, δ denotes constant social discount rate, q is the time- and density-invariant catchability coefficient (as used in the international stock assessment), and c is constant cost per unit of effort.[27] Removing the term capturing

[21] The Törnqvist index, perhaps the most widely used, is a discrete approximation to the Divisia. It has a number of desirable properties: exact (exactly corresponds to a translog functional form to aggregate the inputs comprising effort, a widely used form) and superlative (can approximate a relatively smooth effort aggregator function and allows input substitution) [29].

[22] When the technology has the translog form, the Törnqvist and Malmquist approach yield the same result [28]. The two approaches may differ if efficiency differences are not Hicks–neutral or if there are increasing returns to scale, neither of which is a concern in the case herein.

[23] Both Eqs. (1) and (2) and Eqs. (3) and (4) are shown. Because estimation is typically in logarithm form, Eqs. (1) and (3), the expression after calculation from (1) or (3) is then placed into the form of Eqs. (2) and (4) through the exponential operator. The logarithm form, Eqs. (1) and (3), is commonly interpreted as approximate percentage change from one period to the next. Thus, (1) and (3) measure percentage growth and (2) and (4) measure levels, much like resource stocks estimates provide both growth and level of abundance.

[24] Limited data led to "integrated analysis," which uses all available data, in as raw a form as appropriate, in a single population analysis [25]. Analyses that were traditionally carried out independently are now conducted simultaneously through likelihood functions that include multiple data sources. Stock Synthesis 3 is a widely used approach to integrated analysis [31].

[25] The Durbin–Wu–Hausman version of the test was implemented by including residuals from regressing stock on exogenous variables as additional variables in nonlinear least squares of the fishery production function with the translog effort aggregator function directly inserted into the production function and the likelihood value was compared to that without these additional regressors. Durbin–Watson statistics indicated no serial correlation in the ordinary least squares estimation to obtain the residuals. Instruments included the constant term, Canadian dummy variable, B_{t-1}, P_{t-1}, C_{t-1}, $X_{1,t-1}$, $X_{2,t-1}$.

[26] See Fissel and Gilbert [32] for non-constant rates of technical change and productivity growth. When effort is consistent measured and aggregated from individual inputs according to the theory of economic index numbers, the composite aggregate effort index has allocative efficiency between the different inputs comprising effort.

[27] See Clark and Munro [33] for non-constant P and c, which also gives a non-autonomous model and golden rule.

productivity growth, $e^{(\lambda+M_2\beta_1\psi)t-\mu(t,Z)}$, in the denominator of the marginal stock effect in Eq. (6) (second term from the left) and the entire marginal technology effect (third term from the left) gives the standard specification of the Golden Rule.

Disembodied Hicks neutral technical change, here measured by constant λ, could be expanded to included a quadratic term, λ^2, so that it is time-varying; ideally, $\lambda > 0$, $\lambda^2 < 0$. Step changes [24] and stochastic shocks [32] are also possible. The first term from the left in (6) is instantaneous marginal productivity of S_t, the second term is the modified marginal stock effect (impact of S_t upon costs), and third term is the new marginal technology effect (impact of changes in technical efficiency, given allocative efficiency with effort, and disembodied and embodied technical change upon costs). Assuming constant ψ and M_2 with Cobb–Douglas functional form implies $\Psi_t = e^{M_2\psi_t}$, where Ψ_t is average measure of the level of best-practice technology in time t that depends on the underlying efficiency parameters and age structure of the entire capital stock averaged over all vintages. When measuring productivity growth as a residual, $e^{(\lambda+M_2\psi)t-\mu(t,Z)}$ becomes $e^{\dot\phi}$, where $\dot\phi$ denotes the instantaneous rate of productivity growth as discussed above, which is approximated in discrete time as $TFP_{t,t-1} = TFP_t/TFP_{t-1}$. Overall time-varying catchability $qe^{(\lambda+M_2\psi)t-\mu(t,Z)}$ becomes the product of catchability q that is time-invariant vis-à-vis productivity growth (but could be time varying for other reasons, e.g., environment), and could be density-dependent (neither of which are explicitly specified in q), and a time-varying catchability term $e^{(\lambda+M_2\psi)t-\mu(t,Z)}$, which is productivity growth, and estimated from fishery-dependent data as in economic productivity analyses. Identification issues arising when disentangling temporal changes in productivity and S_t when using fishery-dependent data apply here.[28]

The analysis explores four empirical cases. The base case specifies a constant catchability coefficient and the stock exponent equal to one. The second case specifies the stock exponent equal to 0.9.[29] The third case specifies the catchability coefficient higher than the base case. The fourth case specifies a lower rate of productivity growth. Together, these cases illustrate the impact of the catchability coefficient. There is not a classic no-growth, steady-state solution to B_t^*, but instead a balanced growth path eventually limited by B_t's productivity. The marginal stock effect declines over time, because density-dependent harvest costs are more than balanced by technological change that lowers harvest costs. Over time, both the marginal stock and marginal technology effects decline, requiring continuing increases in the own rate of return to the resource stock, $\partial F/\partial B_t$, given constant δ. Higher rates of δ or productivity growth hasten the decline of B_t^*. The limit rent-maximizing resource stock as time approaches infinity accounting for productivity growth is as follows [3]:

$$lim_{t\to\infty} B_t^* = \frac{K}{4}\left[\left[1-\frac{\delta}{r}\right] + \sqrt[2]{\left[1-\frac{\delta}{r}\right]^2}\right] = \frac{K}{2}\left[1-\frac{\delta}{r}\right], \tag{10}$$

where r denotes the intrinsic growth rate. Because the sum of terms in brackets is less than or equal to 2, $lim_{t\to\infty} B_t^* \le B_{MSY}$, which contrasts with dynamic economic optimum under static technology generally exceeding B_{MSY} [6]. Essentially, over an infinite time horizon, productivity growth erodes costs close to 0, and B_t^* is determined solely by δ, r, K. $\partial B_t^*/\partial t < 0$, so B_t^* declines with productivity growth, and $\partial^2 B_t^*/\partial t^2 > 0$, so that the declining stock levels out for a given rate of continuous productivity growth for the balanced growth path over an infinite time horizon, and the scale, technically efficient, and allocative efficient stock declines at a slower rate toward a stock level for which $\partial F/\partial B_t = \delta$. When $\delta \ge r$, $lim_{t\to\infty} B_t^* = 0$, i.e., extinction is optimal under continuous productivity growth. In the intermediate and realistic case, $0 < \delta < r$ and $0 < lim_{t\to\infty} B_t^* < B_{MSY}$, which contrasts with the orthodox static-in-technology dynamic model in which $B^* > B$ for most reasonable levels of costs and prices and in which density-dependent costs are more important.

The open-access resource stock accounting for productivity growth is as follows:

$$B_\infty = \left(\frac{c}{Pqe^{(\lambda+M_2\psi)t-\mu(t,Z)}}\right)^{1/\alpha}, \tag{11}$$

where again the productivity growth rate is accounted for by $e^{(\lambda+M_2\psi)t-\mu(t,Z)}$.

5. Empirical results and policy implications

This study examines the single-species U.S. and Canadian troll fleets fishing for North Pacific albacore (*Thunnus alalunga*). These fleets form part of the North Pacific albacore fishery of troll, pole-and-line, and other surface gear for Taiwan, Japan, Korea, U.S., and Mexico. Albacore migrate from off Japan across the Pacific at around 40°N to the U.S. Pacific coast along the ocean surface, then some swim north and others south in the California Current. They swim in schools at speeds up to 80 km per hour and are found near dynamically evolving ocean fronts and temperature breaks. The unregulated industry and absence of bycatch imply no regulatory-induced or related directed technical change.

Trolling for albacore entails towing 10–20 lines each rigged with a jig shaped to look like squid on the ocean surface, behind a slow-moving boat. Pole-and-line gear consists of poles rigged with a feathered jig mounted on a barbless hook. For this method to be effective, albacore are attracted to the ocean surface alongside the vessel by chumming with live bait and by the vessel itself. Vessels find the albacore using physical capital embodied with information technology, including sensing devices to find temperature breaks, satellite data to identify ocean fronts, GPS, and echo-sounders. There is minimal catch of other species, so that only a single-product is produced.

Vessels are relatively small and family owned, with U.S. vessel length averaging about 13 m, and harvest albacore from about 160°W to the North American Pacific coast and from 30°N to 55°N. Other than gear and fish-finding equipment, the major on-vessel innovation is an on-board freezer system.

The empirical analysis employs the catch and days fished data used in international stock assessments [34]. From the albacore stock assessment, [30] environmental carrying capacity K=857,138 mt and MSY=105,571 mt. Intrinsic growth is calculated as $r = 4MSY/K = 0.492667458$. International stock assessments also provide exogenous estimates of resource stock biomass for fish age one plus [30] (WCPFC 2014). Cost (c) (US$2001) is set at the 1981–2009 mean, giving $1164.72/vessel-day, where costs include operating costs of fuel, oil, food, gear, and labor [35].[31] P, a weighted average of brine frozen, blast bled, and iced/fresh, is $3515.34/mt.

[28] Technical change is exogenous, a plausible specification in fisheries, since the most meaningful source of new technology is information technology from the aero-space, military, and information technology sectors [3]. This technology is then adapted to fisheries, such as electronic equipment to find fish and aid navigation.

[29] This can be interpreted as the catchability coefficient is a function of stock, i.e., density-dependent catchability.

[30] A comprehensive bioeconomic model for policy rather than illustration entails including productivity estimates of all fleets harvesting albacore and would also specify age-structured population dynamics rather than the Schaefer surplus production model.

[31] Costs were updated through use of economic index numbers, see [3], Appendix 1.

The Canadian and U.S. landings, days, and vessel numbers are also derived from the international stock assessment [34]. The catchability coefficients in the base case were 2.55E-0.6 and in the third case 2.13E-03 (see Table 5.3. in [30]).

The geometric average annual TFP growth with equal weights for US and Canada is 7.12%, which is used as the base case.[32] [33] The cost-share weighted annual TFP growth of both US and Canada is 4.67%, with annual cost shares that change each year and average 91.12% for the US, is used in case four to illustrate the impact of lower technical progress.

Fig. 1 illustrates northern albacore stocks over 100 years assuming logistic growth and constant overall U.S. and Canada fleet productivity growth as the only source of time-varying catchability. Six different stock indices are depicted: optimal stock B_t^* in the three cases, limit stock level $lim_{t\to\infty}B_t^*$, optimum stock without productivity growth (the text-book case), and B_{MSY}.

The results demonstrate first of all that $lim_{t\to\infty}B_t^* < B_{MSY}$. Thus the biomass that maximizes rent when incorporating productivity growth is less than BMSY. Incorporating productivity growth means that BMEY without productivity growth (B^*) is a misleading and false optimum. When accounting for productivity growth, resource stocks and biodiversity in general face greater pressures than realized, and there is an opportunity cost in foregone rent to excluding productivity growth as in the traditional bioeconomic model. The two different economic optimums and economic welfares for society can differ considerably.

Second, the optimal approach paths to $lim_{t\to\infty}B_t^*$ (the limit stock under productivity growth) are different in the four cases. In the base case, the stock begins above BMEY with productivity growth and declines over time to the limit stock. With a stock exponent equal to 0.9, the stock begins much higher, indicating higher marginal stock and technology effects. With a lower catchability coefficient, the marginal stock and technological effects vanish, and the stock begins very close to the limit stock and is therefore not shown in the figure. In the case with lower technical progress, the optimal stock path follows closely the base case.

Fig. 2 illustrates the open access or bionomic equilibrium with and without productivity growth. The open-access, no-growth, steady-state bionomic equilibrium [10] may not even exist. Under productivity growth, the pressures to the resource stock continue, because costs continue to decline and profits are continuously replenished.

Fig. 3 illustrates marginal technology effects (MTE) and marginal stock effects (MSE) over 100 years, showing their relative importance and the decline of the marginal stock and technology effects over time. The marginal stock effect, which is the second term from the left in the fundamental equation of renewable resources or golden rule, Eq. (6), shows the impact of a larger resource stock upon lowering costs, thereby providing an economic incentive to leave more fish in the water. The marginal technology effect, which is the third term from the left in Eq. (6), shows the impact of changes in productivity in lowering costs, thereby providing an economic incentive to harvest fish sooner rather than later. Both the marginal stock and marginal technology effects decline over time, because as productivity grows and with harvesting of the stock, the stock declines and there is a lower impact from fewer fish upon harvest costs.[34]

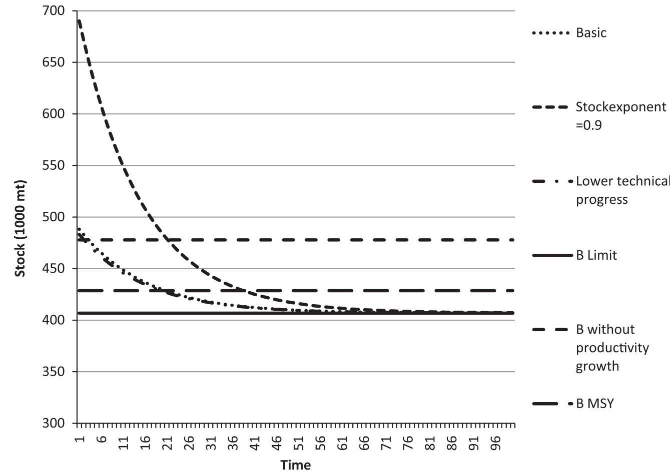

Fig. 1. Stock size paths for fleet productivity growth as the source of time varying catchability.

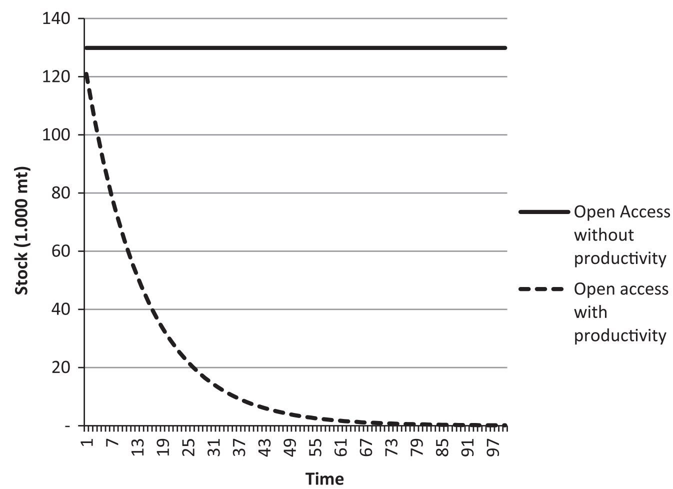

Fig. 2. Open access stock size with and without productivity growth.

In all cases, the marginal stock effects are higher than the marginal technology effects because the productivity growth is lower than the average stock biomass growth. Compared to the base case, both the marginal stock and the marginal technological effects increase with a stock exponent = 0.9 and the differences between the effects narrow. Both effects vanish, as noted, with a lower catchability coefficient, which show no cost or technological gains at higher stock levels and is therefore not depicted in the figure. With lower technical progress, the marginal stock and marginal technological effects are lower than, but similar to, the base case.

6. Concluding remarks

This paper discussed four topics related to productivity growth: productivity growth's impact upon BMEY and bioeconomic modeling; its relationship to time-varying catchability; productivity growth's relationship to fishery-dependent and -independent data and density-dependence in bioeconomic models; and identification in disentangling changes in resource stocks and productivity from fishery-dependent data as well as endogenous regressors in harvest

[32] The TFP measures are derived using Eq. (3) and the cost, landings, and effort data. Taking the exponent of the results gives Eq. (4). These measures are then placed into what is called a chain index, where two adjacent annual TFP measures are multiplied, e.g., $TFP_t * TFP_{t-1}$, for all years. Then chained TFP and its growth reflect the cumulative impact of productivity growth.

[33] The relatively high rate of productivity growth is due to new technology and also likely due to the only economic inputs available were number of vessels and days at sea. A more comprehensive input data set would likely explain more of the sources of growth, and thereby lower the productivity growth rate.

[34] The presence of discounting provides an additional incentive to harvest fish, since revenue received now is worth more than revenue received in the future.

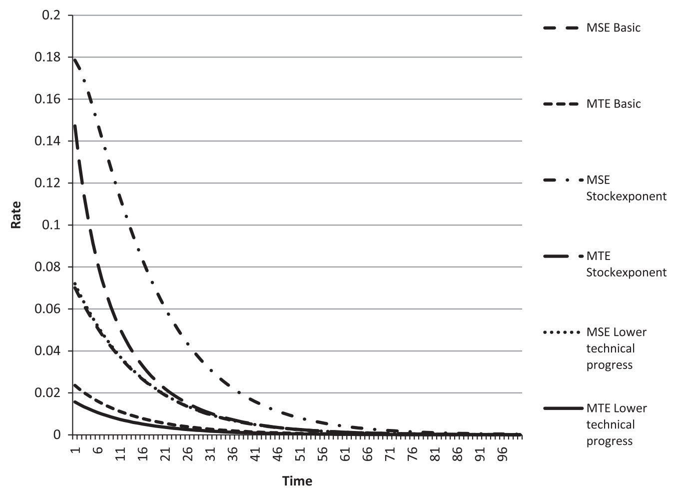

Fig. 3. Marginal stock effects and marginal technology effects.

functions and when standardizing CPUE.

Productivity growth substantially impacts the rent-maximizing level resource stocks, and can lead to BMEY < BMSY, i.e., overfished stocks, counter to conventional wisdom. In a nutshell, productivity growth lowers the costs of finding and harvesting fish over time, and there are now fewer cost savings from leaving unharvested fish in the water to lower costs. The distance between BMEY and BMSY is determined by the rates of intrinsic growth, interest, productivity growth, and discount. The marginal stock effect has no impact upon the final result, and only affects the approach path to BMEY, which is determined by all the biological and economic parameters. Imposing no-growth steady-state bioeconomic equilibrium without accounting for productivity growth gives erroneous results of BMEY > BMSY and misleading policy recommendations, such as underharvesting to save and invest in natural capital to obtain a larger resource stock to lower costs. Productivity growth, as a component of time-varying catchability, also impacts stock assessments.

Applying density-dependent and time-varying catchability in the empirical case leads to quite different approach paths compared to the cases with only time-varying catchability. This empirical case shows that it is optimal to begin with a higher stock level. Generalizing this result is not possible, and more research is needed. However, it reinforces the importance of carrying out an estimation procedure that allows for dependence of time and of resource stock density.

CPUE standardization, estimates of fishery production functions, and productivity measurement all face identification issues in disentangling changes in resource stocks and productivity as well as potentially endogenous regressors (since the regressors, such as effort, are also choice variables). They also face issues of aggregation across different technologies and components of catch and effort. This paper discusses several potential identification strategies.

The study results show that bioeconomic models can give biased results (e.g., BMEY > BMSY rather than BMEY < BMSY) and biased policy advice when not accounting for time-varying catchability—notably productivity growth—and density-dependent catchability. It is fair to conclude that the standard bio-economic model without productivity growth is actually a special case in bio-economics. Biased bioeconomic results and policy advice also arise when not distinguishing between fishery-dependent and fishery-independent data and the implications for catchability, modeling, and applicability of results.

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References

[1] C.W. Clark, Mathematical Bioeconomics: The Optimal Management of Renewable Resources, 3rd ed., John Wiley and Sons, New York, 2010.
[2] J. Conrad, M. Smith, Nonspatial and spatial models in bioeconomics, Nat. Resour. Model. 25 (2012) 52–92.
[3] D. Squires, N. Vestergaard, Technical change and the commons, Rev. Econ. Stat. 95 (5) (2013) 1769–1787.
[4] L.G. Kronbak, D. Squires, N. Vestergaard, Recent developments in fisheries economics research, Int. Rev. Environ. Resour. Econ. 7 (2013) 67–108.
[5] J. Walden, B. Fissel, D. Squires, N. Vestergaard, Productivity change in commercial fisheries: an introduction to the special issue, Mar. Policy (2015), forthcoming.
[6] R.Q. Grafton, T. Kompas, R. Hilborn, Economics of overexploitation revisited, Science 318 (2007) 1601.
[7] World Bank and FAO, The Sunken Billions: The Economic Justification for Fisheries Research, The World Bank, Washington, D.C, 2009.
[8] OECD, The Economics of Rebuilding Fisheries: Workshop Proceedings, Organisation for Economic Cooperation and Development, Paris, 2010.
[9] Global Ocean Commission, The Global Ocean: From Decline to Recovery. Summary Report, 2014, ⟨https://missionocean_www_uploads.s3.amazonaws.com/goc-summary-report-53a8fb89b8cb7.pdf⟩.
[10] H.S. Gordon, The economic theory of a common property resource: the fishery, J. Polit. Econ. 62 (1954) 124–142.
[11] M.J. Wilberg, J. Thorson, B.C. Linton, J. Berkson, Incorporating time-varying catchability into population dynamic assessment models, Rev. Fish. Sci. 18 (1) (2010) 7–24.
[12] R. Hannesson, Bioeconomic production function in fisheries: Theoretical and empirical analysis, Can. J. Fish. Aquat. Sci. 40 (1983) 968–980.
[13] N.-A. Ekerhovd, Gordon D.V. Catch, stock elasticity, and an implicit index of fishing effort, Mar. Resour. Econ. 28 (4) (2013) 379–395.
[14] D. Squires, L.T. Balance, R. Deriso, J. Ianelli, M. Maunder, K. Schaeffer K., Comment on 'Scope and compatibility of measures in international fisheries agreements,' Oxford Economic Papers, 2015, doi: 10.1093/oep/gpv041.in press.
[15] M.N. Maunder, A. Punt, A review of integrated analysis in fisheries stock assessment, Fish. Res. 142 (2013) 61–74.
[16] D. Squires, Productivity measurement in common property resource industries: an application to Pacific fisheries, RAND J. Econ. 23 (2) (1992) 221–236.
[17] M.N. Maunder, J.R. Sibert, A. Fonteneau, J. Hampton, P.A. Kleiber, S.J. Harley, Interpreting catch per unit effort data to assess the status of individual stocks and communities, ICES J. Mar. Sci. 63 (2006) 1373–1385.
[18] R. Hilborn, C. Walters, Quantitative Fisheries Stock Assessment: Choice, Dynamics, and Uncertainty, Chapman and Hall, New York, 1992.
[19] T.J. Quinn, R.B. Deriso, Quantitative Fish Dynamics, Oxford University Press, New York, 1999.
[20] C. Walters, Folly and fantasy in the analysis of spatial catch rate data, Can. J. Fish. Aquat. Sci. 60 (2003) 1433–1436.
[21] M.N. Maunder, A. Punt, Standardizing catch and effort data: a review of recent approaches, Fish. Res. 70 (2004) 141–159.
[22] C. Blackorby, D. Primont, R. Russell, Duality, Separability, and Functional Structure: Theory and Economic Applications, North-Holland, New York, 1978.
[23] M.H. Prager, A suite of extensions to a nonequilibrium surplus production model, Fish. Bull. 92 (1994) 374–389.
[24] B.H. Baltagi, J.M. Griffin, A general index of technical change, J. Polit. Econ. 96 (1) (1988) 20–41.
[25] M.N. Maunder, A. Punt, A review of integrated analysis in fisheries stock assessment, Fish. Res. 142 (2013) 61–74.
[26] C. Hulten, Growth accounting when technical change is embodied in capital, Am. Econ. Rev. 82 (1992) 964–980.
[27] R.M. Solow, Investment and technical progress, in: A. Arrow, S. Karlin, P. Suppes (Eds.), Mathematical Methods in the Social Sciences, Stanford University Press, Stanford, CA, 1960, pp. 339–365.
[28] D.W. Caves, L.R. Christensen, W.E. Diewert, The economic theory of index numbers and the measurement of input, output, and productivity, Econometrica 50 (6) (1982) 1393–1414.
[29] W.E. Diewert, Exact and superlative index numbers, J. Econom. 4 (1976) 52–92.
[30] WCPFC Stock assessment of albacore tuna in the North Pacific Ocean in 2014, WCPFC-SC10-2014/SA-WP-12, ⟨https://www.wcpfc.int/system/files/SC10-SA-WP-01%20%5BBET%20Assessment%5D_rev1_25July.pdf⟩.

[31] R.D. Methot, C.R. Wetzel, Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management, Fish. Res. 142 (2013) 86–99.
[32] B. Fissel, B. Gilbert, Exogenous productivity shocks and capital investment in common-pool resources, Department of Economics, University of California, San Diego, 2010.
[33] C.W. Clark, G. Munro, The economics of fishing and modern capital theory: a simplified approach, J. Environ. Econ. Manag. 2 (1976) 92–106.
[34] WCPFC (Western and Central Pacific Fisheries Commission) Report of the ISC Albacore Working Group for 2010, WCPFC/NC6/IP-02 ⟨http://www.wcpfc.int/system/files/WCPFC-NC6-IP-02%20%5BNP%20albacore%20Report%5D.pdf⟩.
[35] D. Squires, S.F. Herrick Jr., D. Dealy, Colpo D., American Fishermen's Research Foundation, Cost-and-earnings survey of the West Coast albacore troll fleet, 1996–1999 National Marine Fisheries Service, Southwest Fisheries Science Administrative Report LJ-03-01 2003.