Measuring, Interpreting and Monitoring Economic Productivity in Commercial Fisheries

Final Report

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Abbreviations

ABARES	Australian Bureau of Agricultural and Resource Economics and Science
AE	Allocative Efficiency
CPUE	Catch Per Unit Effort
CU	Capacity Utilisation
DEA	Data Envelopment Analysis
FAO	Food and Agriculture Organisation of the United Nations
IND	Index Number Decomposition
PIRSA	Primary Industries and Regions South Australia
QLD DAF	Queensland Department of Agriculture and Fisheries
SE	Scale Efficiency
SFA	Stochastic Frontier Analysis
SPF	Stochastic Production Frontier
TAC	Total Allowable Catch
TE	Technical Efficiency
TFP	Total Factor Productivity
UCU	Unbiased Capacity Utilisation

Executive Summary

This report brings together a body of knowledge from over 30 years of Australian and international research and illustrates how productivity analysis can provide additional insights for fisheries management. Our comprehensive review identifies a maturing of the literature from asking questions simply about 'what' towards 'how' and 'why', with key gaps remaining. Using the findings from the review to inform our methodological approach, we analyse three Australian case studies to illustrate: how different metrics can be used to identify productivity in fisheries; the consistency of these metrics; how they relate to other measures of economic performance; and, where relevant, the impact of productivity measurement on management change. The case studies are the Commonwealth Northern Prawn Fishery, the South Australian Spencer Gulf and West Coast Prawn Fisheries, and the Queensland Spanner Crab Fishery.

The project team is a collaboration of economists, analysts and fisheries managers from the University of Adelaide, CSIRO, ABARES, BDO EconSearch, PIRSA, and QDAF. This allows us to take advantage of different types of data available in our case studies, each with their own unique flavour, but retain a common analytical backbone of using data envelopment analysis to calculate technical efficiency and capacity utilization.

This project demonstrates the variety of questions that can be addressed using productivity analysis, including evaluating the impact of management change, and that quantity-based measures of efficiency (those estimated using quantity data alone without economic data) provide useful measures of aggregate economic performance in some scenarios. We also show that heterogeneity in economic outcomes at the individual level can arise even when inputs and outputs are homogenous, emphasizing that carefully defining the purpose of undertaking productivity analysis is important. The associated guidelines for using productivity analysis in fisheries management are an important resource for industry, managers and policy makers.

Background

Evaluating the performance of fisheries with respect to economic outcomes is crucial for effective fisheries governance. Practical use of economic metrics has, however, been hampered by limited data, due to the costs of data collection and provision. Productivity analysis offers a way to use existing data – on quantities, or values, of inputs and outputs – to determine efficiency levels and variation within a fishery. These measures can then be monitored over time or used to examine the impact of management change to determine where improvements could be made. In the Australian context, productivity analysis has been limited by data access and the use of productivity measures as informative metrics of economic outcomes for ongoing management has not been fully examined. Understanding how productivity analysis can be used to enhance fisheries outcomes is important for industry and policy makers alike.

Objectives

This project has three key objectives:

1. To review the use of productivity analysis as a performance indicator and in management assessment in fisheries and assess the contexts in which it provides additional insights for effective management.
2. To demonstrate the use of productivity measurement and analysis as a performance indicator in three Australian fisheries.
3. To develop a guide for managers to illustrate how productivity analysis can provide relevant and cost-effective economic performance indicators and how these can be used to inform management decisions.

Methodology

To meet the first objective, we conduct a comprehensive, critical literature review complemented by bibliometric analysis of research using productivity analysis in wild-caught fisheries. We identify main methods and metrics, common themes, and policy implications of Australian and international studies. The scope of, and methods used in, the case studies are guided by the foundations contained within, and gaps in the literature; and the guidelines for managers draw upon our own analysis and that of the broader literature.

A variety of methods have been used in productivity analysis, each used to take advantage of aspects of the data or to highlight particular characteristics of the fishery. We use data envelopment analysis to calculate technical efficiency and capacity utilization across each of our three case studies to maintain a consistent methodological approach. In each of our case studies we then illustrate how alternative methods or metrics can address additional questions or provide deeper insight. That is, for the data-rich Northern Prawn Fishery we also: use two alternative modeling techniques (stochastic production frontier and stochastic multi-output distance function analysis); compare quantity-based productivity metrics to measures of economic performance; and evaluate productivity after significant management change. For the SA Spencer Gulf and West Coast Prawn Fishery we use the detailed vessel-level economic information to examine how quantity- and value-based measures may diverge. While in the Queensland Spanner Crab Fishery we investigate spatial differences and management change using a comprehensive history of individual logbook data.

Results

The review shows an evolution in the focus of the literature from early attention on the direct measurement of productivity towards asking questions regarding why and how the measures are at such a level or changes are occurring. Major areas for future research include the need to better understand: the link between technical efficiency, capacity utilization and economic performance; the consistency of productivity indicators when applying different analytical methods; the implications of behavioral responses of fishers; and the impact of dispersion, heterogeneity, inequality and institutions on management outcomes.

The case study analyses show that in a data-rich fishery, the Commonwealth Northern Prawn Fishery, technical efficiency (from quantity data) is a consistent measure of productivity that is positively correlated with economic performance. We also find that management intervention directly addressing input quantities (buybacks) is related to a strongly positive increase in productivity in this fishery. For an input-managed fishery with rich economic data but much smaller in size, the SA Spencer Gulf and West Coast Prawn Fisheries, technical efficiency (from quantity data) exhibits less variation than value measures, which indicates that heterogeneity in economic outcomes can arise at the individual level even when quantities are relatively homogeneous. The Queensland Spanner Crab Fishery's extensive logbook records of catch and effort data reveals relatively low levels of technical efficiency, limited variation spatially across management areas and across time, indicating scope for further economic improvements now that the stock status has improved.

Implications

This study shows that productivity analysis in fisheries is a growing and deepening area of research. The methodologies available have progressed to account for the complexities of fisheries as a natural resource industry within a changing physical and economic environment. The statistical methods allow robust analysis of individual data to provide consistent measures of aggregate performance of fisheries over time and space. In concord with wider economic and social analysis, there remain gaps regarding the impact of dispersion, heterogeneity, inequality and institutions.

The advantage of using a common, primary method of analysis is that we can see how different types of data influence the types of questions that can be addressed with the same methodology.

Complementing the primary analysis with additional investigations of relevance to each study and data – management change, alternative analytical specifications, comparison with economic performance – allows us to demonstrate how productivity analysis can be used to monitor performance and guide management decisions.

Evaluating the use of quantity-based productivity analysis within our case studies indicates that they can provide effective measures of aggregate economic performance when appropriate histories of individual data are available. The relationship is strongest with short-run measures of economic performance, indicating that quantity-based productivity metrics can be an effective indicator.

Economic performance depends on both quantity and value and fishers will use the mechanisms available to them to meet their individual objectives. As such, if a fishery is managed with both input and output controls, then fishers who seek to increase their own profits will necessarily need to do this by reducing input costs or seeking higher output prices. Increased heterogeneity in economic outcomes is therefore likely where individual objectives diverge.

Evaluating management and management change in fisheries depends upon the objectives of management. Productivity analysis can be used to identify opportunities to increase efficiency at the aggregate level. The buybacks in the Commonwealth Northern Prawn Fishery are found to be associated with improvements in both quantity- and value-based measures of performance. Management change in the Queensland Spanner Crab Fishery has no discernible impact on efficiency, despite achieving positive outcomes for stock status. This highlights the need to consider both biological and economic outcomes, and to determine appropriate methods to assess management against these multiple objectives.

Each of our case studies is chosen to reflect typical types of fisheries and data available in Australia. The Commonwealth study has both quantity and value data from individual boats over a long period of time, allowing the widest range of analysis. The SA study has fewer time periods and individual boats are not identified across time but the detailed survey allows clear evaluation of variation within the economic outcomes. The Queensland study has a long history of individual quantity data from logbooks, which provides an opportunity to evaluate efficiency across both space and time, although understanding the implications for value-based outcomes is not yet possible. A pleasant surprise in our analysis is the glass-half-full outcome of what can be evaluated from data that does already exist within Australian fisheries, if access is possible.

Recommendations

This study demonstrates that productivity analysis can be used to address a variety of questions in fisheries management including: evaluation of the impact of management change; and identifying potential for improving economic outcomes. It also identifies that quantity-based measures of productivity can be used as effective indicators for fisheries under relatively stable management, biomass and market conditions. In addition, we illustrate the type of analysis that can be undertaken using quantity data that has been collected within Australian fisheries and what can be done when additional economic data is available. Given this, managers and industry may wish to consider:

- Greater use of productivity analysis to evaluate the impact of management change and identify fisheries for which productivity is low;
- Implementing ongoing productivity analysis as a monitoring tool in fisheries with long panels of data with associated management targets; and
- Using existing data, such as from logbooks or existing economic surveys, as a starting point and complementing this with additional economic data as it becomes available.

Keywords

Economic productivity; efficiency; capacity utilization; data envelopment analysis; economic performance; Commonwealth Northern Prawn Fishery; South Australian Spencer Gulf and West Coast Prawn Fisheries; Queensland Spanner Crab Fishery

Introduction

Background

The development of indicators to measure and monitor the performance of fisheries against economic objectives continues to challenge fisheries managers. To date economic metrics have focused on various measures of profitability, and this has been limited to relatively few fisheries due to the costs and time involved in collecting the information.

Productivity analysis provides an alternative approach to measure and monitor performance in fisheries. It is an economic analysis method that can be used to estimate how the level and combination of inputs used by fishers affects their level of output, revenue or profitability. From this, the level of efficiency within a fishery can be determined, and depending on the data type (e.g., available time series data) changes in the efficiency level over time can be monitored. The role of fishery management in influencing the efficiency of a fishing fleet can also be directly determined. Furthermore, measures of capacity utilization provide information on the level (and changes in) excess capacity, which can be used to develop a proxy measure for the optimal fleet size.

Many productivity measures can be derived from available logbook data, while more detailed measures can be obtained from the full economic data (e.g., socio-economic characteristics of fishers, vessel characteristics, environmental conditions). These approaches can also provide information about fisher behavior, such as targeting ability in multispecies fisheries, and their response to changes in price and costs, as well as offer information on what is driving changes in profitability (e.g., prices, costs or management). In addition, appropriate measures can be identified to inform management (e.g., via monitoring or evaluation of interventions) across commercial and other fisheries sectors.

The application of these techniques in Australian fisheries has been limited, and their ability to provide cost-effective information that is useful for fishery management has not been fully examined. Outside fisheries, productivity has proven to be a useful economic indicator and its potential in Australian fisheries needs to be assessed. This project will meet this need by asking: In what contexts do indicators of productivity and productivity change provide a useful addition to other measures of fisheries economic performance?

Need

The FRDC's November 2018 call for EOI asked for a project to:

1. Review the use of productivity analysis as a performance indicator and in management assessment in Australian fisheries and internationally.
2. Select and execute 2-3 contrasting case studies of commercial fisheries to demonstrate the use of productivity measurement and analysis as a performance indicator and to assess the effect of a management change. Useful contrasting case studies may include, for example, single species and multi-species fisheries.
3. Drawing on 1. & 2., and the wider literature on productivity, develop a simple decision tool allowing managers to determine whether productivity is a relevant and cost-effective economic performance indicator.

An earlier FRDC project (Project 2008/306) aimed to improve the understanding of economic considerations into marine management through training and network building. The present project is a continuation of the earlier work but in the specific area of productivity analysis in fisheries management. The particular focus is on analysis in the Australian context regarding management objectives and data availability.

Different methods can be applied to derive productivity indicators, with method selection typically based on the availability of data and characteristics of the fishery. Comparison of results across productivity studies needs to be conducted with caution, acknowledging potential issues with data availability or quality and the assumptions of the selected methods.

By choosing three different case studies within Australia, we seek to: understand productivity in those individual fisheries; gain information about the consistency of productivity indicators when we apply different methodologies across the case studies; and undertake a comparison of productivity indicators for the fisheries selected for the case studies. This will allow us to outline in which data situations simple productivity measures are likely to be sufficient for effective decision making and when more data intensive methods are likely to be required.

The broader potential for productivity analysis to monitor performance and provide additional insights has not generally been explained to managers or other stakeholders. This project develops a guide to what different productivity analysis approaches can provide for managers, and how the basic metrics produced can be used. It is not a technical guide to undertake the analysis, although descriptions are included in this report, but a guide to how to interpret the results.

The case studies and guidelines for managers contribute particularly to FRDC's R&D Plan enabling strategies I and IV.

Strategy I: Drive digitisation and advanced analytics – by showcasing the use of existing data and using consistent analytical approaches.

Strategy IV: Build capability and capacity – by analysing particular fisheries and developing guidelines for managers on the use of productivity analysis in fisheries.

Objectives

This project has three key objectives:

1. To review the use of productivity analysis as a performance indicator and in management assessment in fisheries and assess the contexts in which it provides additional insights for effective management.
2. To demonstrate the use of productivity measurement and analysis as a performance indicator in three Australian fisheries.
3. To develop a guide for managers to illustrate how productivity analysis can provide relevant and cost-effective economic performance indicators and how these can be used to inform management decisions.

The comprehensive review of the literature is global but highlights Australian research. The three case studies are the: Commonwealth Northern Prawn Fishery; South Australian Spencer Gulf and West Coast Prawn Fisheries; and Queensland Spanner Crab Fishery. These case studies were chosen to highlight different aspects of analysis with a variety of data availability.

Method

Overview

This project has three distinct parts, one for each objective. In this section we will briefly describe the overall method and approach for the project. In subsequent subsections we detail the method for the literature review; describe productivity measures and methodologies; and specify the particular productivity analysis approaches used in the case studies.

Part I: Review the use of productivity analysis as a performance indicator and in management assessment in Australian fisheries and internationally.

Economic performance metrics for Australian fisheries have focused on financial measures of profitability to measure fishery performance, while the use of productivity to measure and monitor performance in Australian fisheries is less common. Productivity measures include technical efficiency, capacity utilisation, scale and allocative efficiency. Our aim is to identify existing Australian studies, common themes, and policy recommendations and to discuss how these relate to the international body of literature about managerial aspects of fishery productivity.

The review provides a survey of the literature of productivity analyses of fisheries worldwide, including Australia. The findings then guide and inform the scope of and specific methodology for the case studies (Part 2) and contribute to the development of guidelines for the use of productivity indicators in management (Part 3).

Part 2: Undertake three contrasting case studies of commercial fisheries to demonstrate the use of productivity measurement and analysis as a performance indicator.

The measurement of productivity is important for understanding the economic condition of firms, industries and regions, and how changes in productivity relate to changes in economic performance. Different methods can be applied to derive productivity indicators, with method selection typically based on the availability of data, characteristics of the fishery and purpose of the analysis. Comparison of results across productivity studies needs to be conducted with caution, acknowledging potential issues with data availability or quality and the assumptions of the selected methods.

We use existing data to conduct productivity analysis and compare this to standard management data for each of three Australian case studies. This allows us to: understand what additional knowledge more nuanced productivity analysis gives and determine when the additional insights are most valuable; and shows how productivity metrics can be potential indicators of economic outcomes for monitoring purposes. The three studies were chosen to highlight how different types of data can be used, whilst retaining a common methodological backbone.

--The Commonwealth Northern Prawn Fishery is a data-rich fishery with vessel level economic and logbook data. These data will be used to estimate productivity measures using the widest variety of methods to assess consistency of productivity and economic performance measures and to highlight the unique additional information that each approach can provide. The impact of management change is investigated.

--The SA Spencer Gulf and West Coast Prawn Fishery has detailed vessel level quantity and value information, but is not collected annually, which limits the ability to directly compare some methods. Overall trends and the implications of the different approaches for management can be derived and additional heterogeneity is investigated.

--The Queensland Spanner Crab fishery has a long series of individual logbook data across five regions but has no economic value data (e.g., revenue, production costs). This fishery is used as an example of how quantity-based measures of productivity can highlight the relationship between inputs and outputs, and whether this is affected by management change.

Part 3: Develop a guide for managers to illustrate how productivity analysis can provide relevant and cost-effective economic performance indicators and how these can be used to inform management decisions.

Findings and results from Parts 1 and 2 provide the basis for developing a guide for fishery managers in Australia about: the usefulness of productivity analysis for fishery management decisions; the use and interpretation of productivity indicators; how productivity measures can be used to monitor the performance of fisheries; and potential data requirements for the development of productivity indicators.

Literature Review Method

Two complementary methods were used to review the literature in the field of productivity and efficiency analysis in the context of fisheries and aquaculture industries: a search of databases and additional identification of reports with subsequent summaries; and a bibliometric analysis of the peer-reviewed literature.

Database search and summary

Google Scholar and EconLit databases were searched for keywords using the following search terms: [efficiency OR effectiveness OR productivity] AND [fish*]. These searches were supplemented with references identified therein, particularly for government reports or working papers. A few key references regarding productivity theory or applications outside of fisheries are included but the vast majority are fisheries specific. The [fish*] search allowed identification of aquaculture studies but purely engineering-type technical studies were discounted, as were case studies outside of fisheries that use Fisher index methods.

Approximately 350 references were recorded with standard citation characteristics and briefly summarised by: Question; Location; Fishery; Time Period; Data; Management; Method; Conclusion; and Issues Raised/What's Missing. All these contributed to the overall summaries, themes and trends. A subset of more than 100 references were identified from the literature review as being of particular significance, either due to developing a new methodology, providing a review or overview of the literature, for being a clear example of a method, or for examining Australian fisheries (28 items). This subset of fisheries studies, and some wider references, are explicitly referenced in the following sections.

Bibliometric analysis

A bibliometric analysis was also performed using the VOSViewer software (van Eck and Waltman 2020). VOSViewer is a tool for creating maps based on bibliometric network data that is published in academic databases (e. g., Web of Science, Scopus, Dimensions, and PubMed files). The software can be used for identifying important publications or authors and their links or major themes that occur in the literature. However, the tool does not allow a detailed analysis of trends within the literature or the identification of research gaps. The analyst chooses the criteria on which to determine similarity (e.g., authors, keywords, journal) and the software identifies clusters within those criteria that are linked; the clusters are not pre-determined by the analyst so interpretation of the clusters and links is still required.

To retrieve bibliometric data of publications in the field of fishery productivity and efficiency analysis the Web of Science database was accessed. The advanced search function was used to search the Web of Science for terms such as: KP=((productivity OR efficiency) AND (fisher* OR aquaculture)) or TS=((productivity OR efficiency) AND (fisher* OR aquaculture))). The search resulted in a sub-sample of 256 publications (75% of the full set of references) covering relevant observations listed during 1987 to October 2020. This sub-sample of references used in the bibliometric analysis is limited to publications included in the databases due to the need to include keywords and references, as supported by the software (e.g., journal articles, books, chapters). Reports and other type of publications (e.g., theses) are not listed in databases that VOSViewer supports and cannot be included in the analysis. While academic publications that contribute to the theoretical foundations of productivity analysis but do not have 'fish*' or 'aquaculture' in the titles or keywords are included in the summaries, they are not assessed in the bibliometric analysis but will appear in the cross-citation analysis if they contribute to multiple fish* or aquaculture publications.

The complete bibliometric data set (e.g., author, title, keywords, abstract, all citations) of each publication was downloaded from the Web of Science and uploaded into the VOSViewer for analysis.

Productivity Measures and Methodologies

Productivity analysis is most simply defined as some metric of output with respect to the input used. Efficiency analysis is a complementary part of productivity analysis. Efficiency is measured as how far from the most productive (set of) vessel(s) is another vessel.[1]

In the abstract case of a single output and a single input, where each are controllable, uniform and measurable, productivity calculations are straightforward (but likely uninteresting). In practice, multiple inputs and multiple outputs that are measured with different units are the norm, some inputs cannot be measured, random error in measurement occurs, the production process is subject to slight variations, and biological and environmental inputs cannot be fully controlled.

Fisheries productivity and efficiency analysis is a complex task due to the difficulty of measuring key inputs (i.e., fish stocks), the joint production processes of multi-species fisheries, and the importance of the environmental conditions (Squires 1994, Jin et al. 2002, Kirkley et al. 2002, Felthoven and Morrison Paul 2004). In addition, the objectives of measuring productivity may differ if value (profits, revenues and costs) or quantities of output (tonnes caught) or inputs (employment or physical capacity) are to be considered.

Within the field of productivity analysis, a range of measures and methodologies have been developed to account for different types of queries. The application of measures and methods typically depends on the specific matter to be investigated and on the availability of data. Productivity metrics have proven to be useful economic indicators in areas such as: individual labour or firm productivity; manufacturing and construction industry productivity, or public health sector productivity (Mahadevan 2002, Hu and Cai 2004, Liu et al. 2013, Nazarko and Chodakowska 2015, Cantor and Poh 2017, Mardani et al. 2017, Grifell-Tatjé et al. 2018).

In Australia, the Productivity Commission has an ongoing reporting function and uses various measures of productivity to do so. For instance, aggregate productivity measures from the Australian Bureau of Statistics are unpacked and interpreted in PC Productivity Insights (Productivity Commission 2022). Simple proxy indicators for the efficiency of Australian government services, such as school expenditure per student, police expenditure per person, cost per social housing dwelling, are presented in conjunction with indicators regarding equity and effectiveness in the annual Report on

[1] Coelli et al. (2005) is an excellent general reference book for methods and applications. Grifell-Tatjé et al. (2018) provides an overview of challenges in productivity analysis in general.

Government Services (SCRGSP 2022). In addition, the Productivity Commission has an ongoing research program in which it has analysed trends in, and determinants of, productivity in prominent sectors including financial services, manufacturing, utilities, hospitals, and mining (Topp et al. 2008, Forbes et al. 2010, Topp and Kulys 2012, Barnes et al. 2013, Zhao et al. 2016). Furthermore, as part of the public inquiry role, marine fisheries and aquaculture were subject to an inquiry in 2016. This inquiry was largely descriptive in nature, with a focus on general actions to improve productivity and reduce unnecessary regulation but without direct metrics of performance (Productivity Commission 2016).

Common measures used in productivity analyses include: catch per unit effort; total factor productivity; technical efficiency; capacity utilization; scale efficiency; and allocative efficiency. Methods to derive these measures include: data envelopment analysis; stochastic frontier analysis; and index number decomposition. The following sections offer a brief summary of these measures and methods.

Catch per unit effort

Catch per unit effort (CPUE) is understood as the quantity or value of catch, either aggregated or for a specific species, divided by a measure of input. Typically, the measure of input is the number of fishing days.

An advantage of nominal CPUE is that it can be derived with readily available data. The disadvantage of this measure is that the causes of changes in CPUE cannot be identified. For instance, CPUE may rise due to improvements in fishing technology or skill, or due to a larger biomass as a result of favourable oceanographic conditions or management changes. In addition, offsetting changes, such as technology advancing while biomass falls may be hidden in a constant CPUE. Compositional changes in outputs in multispecies fisheries or, if catch is measured by revenue, rising prices but falling catches may also hide important underlying changes in productivity.

While accounting for other inputs is not usually directly done within a nominal CPUE calculation, an average CPUE can be calculated for subsets of vessels or gear-types to account for differences in capital inputs. CPUE can also be calculated by dividing catch by a measure of biomass, but this assumes a constant relationship between biomass and catch-rate.

CPUE can be used to compare average productivity of a group of fishers across time and individual CPUE can be compared to this average, or any indicator vessel. Determining why there are differences across time, or compared to others, requires further information.

CPUE can be calculated simply as a ratio in a spreadsheet, once the output and input measure are determined. CPUE is useful as a generic, relatively low-cost measure of productivity across time if not included inputs and production processes remain unchanged. Studies which have estimated the CPUE as part of a productivity analysis of fisheries include Thoya and Daw (2019) and Islam et al. (2011).

Total factor productivity

Growth accounting is a method to estimate output as a function of known inputs, and where total factor productivity (TFP) is calculated as the growth (or difference) in output that is not explained by a growth (or difference) in inputs. It is a productivity measure involving all factors of production (Coelli et al. 2005). Compared to CPUE, multiple inputs can be included, and biomass can be directly incorporated. A production function (which is a functional relationship between input used and output produced) is hypothesised, for instance, that output is a multiplicative function of the inputs. How important each of the inputs are in the production process can be estimated and the aggregate level of technological progress or know-how is projected as what cannot be explained by input use alone.

An advantage of growth accounting estimation is that the measure of technological progress can be estimated for different time periods or subsets of vessels. These measures can be compared to assess where the differences occur. A disadvantage of this productivity measure is that the form of production process must be hypothesised, for instance, in which ways the inputs multiply or add together. Furthermore, it is difficult to compare productivity for different subsets of fishers as the value of technological progress can only be compared for fishers in the same group. Growth accounting can be performed with a standard statistical analysis program (e.g., R or Stata) once the production function is determined.[2]

If firm- or vessel-level data are available, an analysis can be performed at that level, otherwise aggregate data can be used for aggregate trends. TFP is helpful as an aggregate measure of productivity across time.

Studies that have used growth accounting to estimate a productivity measure for fisheries include Squires (1992) and Eggert and Tveterås (2013). In Australia, TFP has been estimated for several Commonwealth managed fisheries and has been undertaken as part of the ABARES fisheries economics indicator report series in recent years. Key examples include: Perks et al. (2011), Bath et al. (2018) for the Southern Eastern Scalefish and Shark Fishery (SESSF); Bath et al. (2019) for the NPF; and Mobsby and Bath (2018) for the Eastern Tuna and Billfish Fishery (ETBF). Estimates of TFP in other Commonwealth fisheries has been undertaken by Stephan (2013) and Stephan and Vieira (2013).

Technical efficiency

The quantitative estimation of technical efficiency (TE) derives from the earlier work by Farrell (1957), who defined technical efficiency as the difference between what a firm currently produces with the current set of inputs, and the production frontier defined as the maximum output that could be produced given those same set of inputs. This later became known as an output-oriented efficiency measure. Farrell (1957) also considered the case of an input-oriented efficiency measure, where efficiency was defined in terms of the ratio of the current input use to the minimum amount of inputs required to produce the same level of output.

This is illustrated in Figure 1. The production frontier is defined by firms with the greatest output for a given level of inputs. For an output-oriented efficiency analysis, firms that have a lower output given their input level fall below the production frontier. The level of inefficiency is determined by the

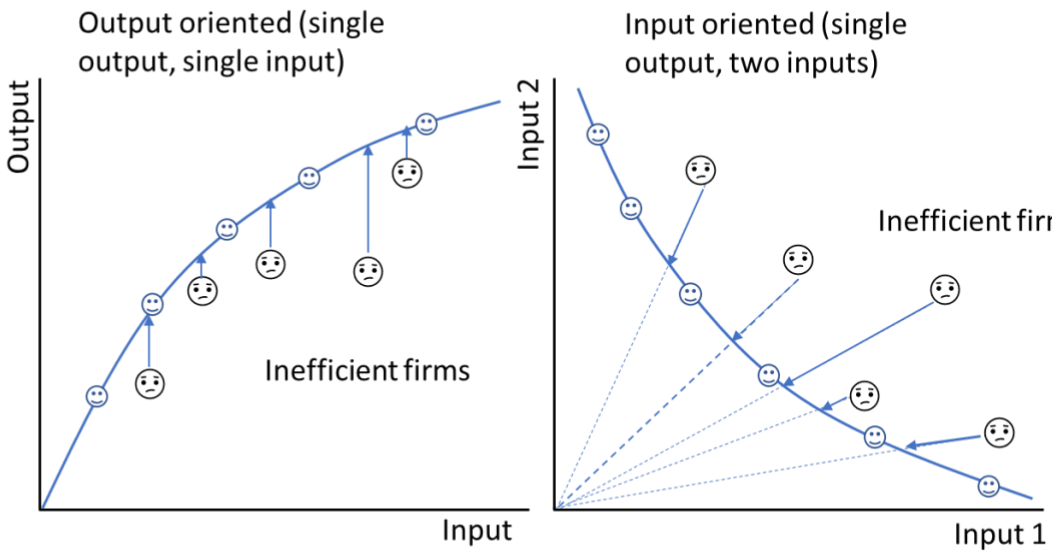

Figure 1. Technical efficiency

[2] Depending on the type of data, the statistical analysis may potentially be conducted in a spreadsheet.

difference between what they currently produce and what they could produce if fully efficient (the vertical lines). For an input orientation, the efficient isoquant is again determined by the set of efficient producers. The level of inefficiency of the inefficient firms is based on the ratio of the Euclidean distance to the frontier isoquant and the distance to the origin.

Technical efficiency is a necessary component of economic efficiency; for a firm to be economically efficient it must also be technically efficient (Yotopoulos and Lau 1973, Page 1980). Given this, changes in the level of technical efficiency provide an indication of changes in economic efficiency.

Internationally, technical efficiency has been estimated for a wide range of fisheries and aquaculture systems in both developed and developing countries. Most studies have focused on factors affecting technical efficiency, particularly fisheries management (e.g. Pascoe et al. 2001, Fousekis and Klonaris 2003, Squires et al. 2003, García del Hoyo et al. 2004, Tingley et al. 2005).

In Australia, technical efficiency has been estimated for fisheries in Queensland (Pascoe et al. 2017), NSW (Greenville et al. 2006), Tasmania (Rust et al. 2017) and a number of Commonwealth managed fisheries, including the Northern Prawn fishery (Kompas et al. 2004, Pascoe et al. 2007, Pascoe et al. 2012, Pascoe et al. 2018), Torres Straits Rock Lobster fishery (Pascoe et al. 2013), SESSF (Green 2016), ETBF (New 2012). Technical efficiency has also been estimated for the Sydney Rock Oyster industry (aquaculture) (Schrobback et al. 2015).

Capacity utilisation

Capacity utilisation (CU) is a measure of the extent to which fixed inputs are fully utilised. That is, the extent to which the firm is operating at full capacity. In the fishery case, a vessel that is operating only part time (for example) will not be operating at its full capacity. Capacity utilisation is measured in the same manner as technical efficiency, although only fixed inputs are considered (rather than both fixed and variable). As the 'raw' measure of capacity utilisation also includes a component of technical inefficiency, an 'unbiased' measure of capacity utilisation needs to be derived by removing this component (Pascoe and Tingley 2007). Hence, the estimation of capacity utilisation also requires the estimation of technical efficiency.

The measurement of capacity utilisation also provides a number of other useful measures. First, capacity utilisation measures can be used to estimate the total capacity of the fishing fleet. That is, the potential catch that could be taken if all vessels were operating at full capacity. The difference between the capacity output and the current output provides a measure of the level of excess capacity in the fleet.

Capacity utilisation and excess capacity exist due to several factors. In a quota managed fishery, for example, if the capacity of the fleet exceeds the TAC, then vessels will be underutilised. In input control fisheries, again if the potential fishing effort that could be applied by the fleet exceeds the limit, vessels will be underutilised and excess capacity will exist. In either management system, a price (or cost) change may also affect capacity utilisation. Assuming fishers are profit maximisers and equate marginal revenue to marginal cost, if prices decrease, then marginal revenue decreases and fishing effort will decrease. Similarly, if costs increase, then fishing effort will decrease. In both cases, capacity utilisation decreases in line with the change in economic circumstances. Hence, in theory, capacity utilisation provides an indicator of the economic performance of the vessel/fleet.

While (unbiased) capacity utilisation and technical efficiency are similar in concept, they may move in different directions. Vessels may be efficient, but operating at less than full capacity, or may be inefficient and operating at full capacity. Relative changes in capacity utilisation and technical efficiency provide information as to drivers of economic performance. For example, in the case of price decreases, this will reduce capacity utilisation but not necessarily efficiency. Conversely, a management change may impact technical efficiency but not capacity utilisation, or may impact both.

Capacity utilisation can also provide a measure of what an optimally sized fleet may look like under current conditions (Färe et al. 2000). If all vessels operated at their full capacity, then fewer would be required to take the same catch as the current fleet. For example, Tingley and Pascoe (2005) used this approach to estimate the optimal Scottish fishing fleet under different ITQ scenarios, while Kerstens et al. (2006) applied the approach to the Danish fisheries, identifying substantial excess capacity and the potential industry structure at full capacity.

The estimation of capacity utilisation was promoted by the FAO as part of its international plan of action on the management of capacity (FAO 1999). Since then, estimates of capacity utilisation were widely undertaken across the EU (e.g. Tingley et al. 2003, Vestergaard et al. 2003, Espino et al. 2005, Pascoe and Tingley 2006, Lindebo et al. 2007, Tsitsika et al. 2008, Idda et al. 2009, Castilla-Espino et al. 2014, Pinello et al. 2016), Asia (e.g. Squires et al. 2003), the US (Kirkley et al. 2002, Felthoven et al. 2009) and Canada (Dupont et al. 2002, Squires et al. 2010). The estimation of capacity utilisation has also been applied to aquaculture (Aripin et al. 2020).

In Australia, Pascoe et al. (2013) used capacity utilisation estimates to examine the likely consequences of moving to an ITQ system in the commercial fleet operating in the Torres Strait Rock Lobster fishery. Rust et al. (2017) looked at the impact of introducing ITQs on capacity utilisation and excess capacity in the Tasmanian Rock Lobster fishery. Schrobback et al. (2015) estimated the level and drivers of capacity utilisation (and efficiency) for the Sydney Rock oyster industry.

Scale efficiency

Scale efficiency (SE) is a measure of the firm relative to its optimal scale (size), and is a measure of the efficiency loss that occurs due to a deviation from the technically optimal production scale (Rust et al. 2017). Optimal in this case refers to the point at which returns to scale are constant (Frisch 1965). With increasing returns to scale, the firm would be better off being larger; with decreasing returns to scale, the firm would be better off being smaller (in terms of productivity measures relating outputs to input use). The point of constant returns to scale is also the point of the minimum cost curve, this being the link between productivity analysis and economic performance.[3]

Scale efficiency is estimated as the difference between the efficiency estimate assuming the production process is characterised by constant returns to scale, and that assuming the production process is characterised by variable returns to scale. In Figure 2, the blue firms are all technically efficient and define the production frontier assuming returns to scale can vary. However, they are not scale efficient, as they are subject to either increasing or decreasing returns. The green firm is both technically and scale efficient as it lies on the frontier at the point of constant returns to scale. The yellow firm is technically inefficient, but is close to being scale efficient (i.e., about the right size but operating inefficiently). The black firms are both technically and scale inefficient.

Scale efficiency measures provides managers with an indication as to which boats are likely to be operating at the least cost point of the cost curve (if efficient). Potentially, as the fleet adjusts over time, it is likely that vessel size will start to converge to this optimal scale.

Scale efficiency has been estimated for a number of fisheries internationally as part of the efficiency analysis process (e.g. Idda et al. 2009, Ceyhan and Gene 2014, Pinello et al. 2016, Madau et al. 2018) as well as for aquaculture (Aripin et al. 2020). In Australia, scale efficiency has been estimated for the northern prawn fishery (O'Donnell 2012, Pascoe et al. 2012), Tasmanian lobster fishery (Rust et al. 2017) and Sydney rock oyster industry (Schrobback et al. 2015).

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[3] Returns to scale describes the relationship between changes in fixed inputs and outputs. Variable returns to scale allow for increasing, constant and decreasing returns within the same fleet. Increasing returns occurs when output increases (decreases) more than proportional with an increase (decrease) in fixed input use (e.g., boat size), all else being equal. Decreasing returns to scale exists when output increases (decreases) at a lesser rate than fixed input use. Constant returns exist when the rate of output and input change are the same.

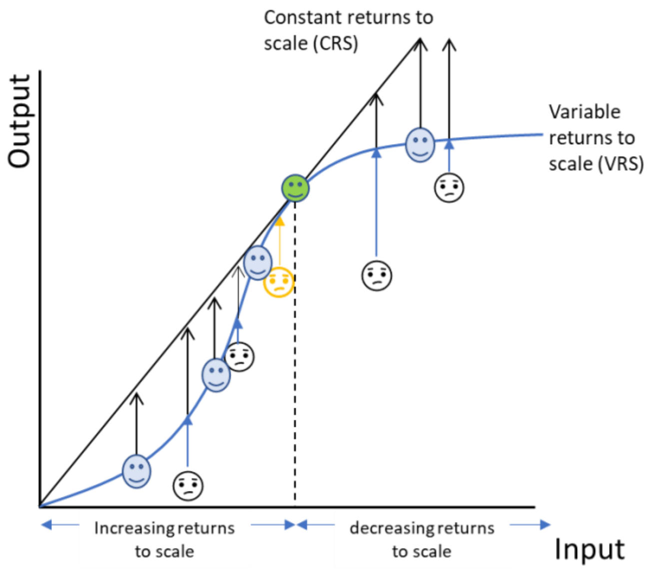

Figure 2. Scale efficiency

Allocative efficiency

Allocative efficiency (AE) is also a key component of economic efficiency; to be economically efficient a firm must not only be producing the most outputs given the level of inputs, but also must be producing the revenue-maximising combination of outputs with the cost minimising combination of inputs. In addition to the technical inputs required for estimating technical efficiency (i.e. catch of different species, different levels of input use), allocative efficiency also requires information on both input and output prices.

Allocative efficiency in fisheries is mostly estimated for multispecies fisheries where there is the potential for different combinations of catch (e.g., through fishing in different metiers), and is usually focused on output mix rather than input mix. Examples include Lindebo et al. (2007), Ceyhan and Gene (2014) and Asche and Roll (2018) in commercial fisheries; and Karagiannis et al. (2000), Ferdous Alam and Murshed-e-Jahan (2008) and Aripin et al. (2020) in aquaculture. Only a limited number of fisheries studies have assessed allocative efficiency for both inputs and outputs (e.g. Herrero et al. 2006, Kumbhakar et al. 2013). In Australia, allocative efficiency has only been estimated for the Sydney rock oyster industry (Schrobback et al. 2015).

Data envelopment analysis and stochastic frontier analysis

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are methods that allow us to measure productivity compared to a frontier.[4] This frontier can be defined by output, that is, the maximum output that can be produced with a given set of inputs; or by inputs, that is, the minimum inputs that are needed to produce a given amount of output. The frontier is defined as part of the calculations by finding the vessels that produce the most output for the given inputs (or use the least inputs to produce the given outputs) and the outputs and inputs can be defined by quantities or by values. Pascoe and Tingley (2007) provides a clear outline of each method.

The key advantages of DEA and SFA over CPUE is that multiple inputs can be included and DEA can also include multiple output.[5] Compared to the growth accounting method of estimating TFP, different

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[4] Stochastic frontier analysis is also referred to as stochastic production frontier (SPF) analysis.

[5] Modern methods of SFA can also incorporate multiple outputs.

production methods can be used by different vessels, that is, a vessel that uses more labour and less equipment can be equally as productive as a vessel that has replaced some labour with machines.

The frontier is estimated from the data, then productivity of each vessel is determined by comparing the distance from the frontier. The overall efficiency of a fleet can then be determined by the average distance to the frontier. The efficiency can be broken into technical, scale and allocative efficiency: that is, not only how far from the frontier a vessel is given its mix of inputs and outputs; but also whether the vessel should increase or decrease production size; and how the mix of inputs and outputs could be adjusted to increase efficiency. This can be used to answer questions regarding how much inputs can be reduced whilst retaining the same level of output if all vessels operated like the most efficient ones. In addition, the frontier can be estimated at different points in time to see how it has shifted. If regulation is such that a profit maximization or a cost minimization objective is an appropriate assumption, estimating DEA or SFA with profit or cost functions is possible and allows consideration of both price and quantity effects (Felthoven and Morrison Paul 2004).

Comparing DEA and SFA, the advantage of DEA is that it is non-parametric, that is, a production function does not need to be specified in the estimation process whereas a functional form must be pre-specified for SFA.[6] Choosing the most appropriate functional form for SFA from a set of flexible options is part of the estimation process. In addition, DEA can directly allow for multiple outputs whereas SFA can only have one measure of output, although this can be an aggregated measure such as total revenue, total tonnes, or a Divisa index (Hulten 1973) where catch is weighted by revenue share. The disadvantage of a traditional DEA is that it is deterministic, that is, there is no allowance for random shocks to the production process outside the control of the fishers. Statistical advances have allowed more recent DEA methods to allow for these shocks (Walden 2006). An important advantage of SFA is that the coefficients of the production (or profit or cost) function are estimated directly as part of the analysis (Kalirajan 1990). This means that the marginal contribution of each input to overall output can be estimated as well as the efficiency measures.

DEA and SFA estimate frontiers using both variable and fixed inputs. Fixed inputs, such as the vessel size or gear-type, reflect the capacity of the vessel (and in many management systems 'capacity' is represented by physical boat measures such as boat size, engine power or combinations of them both). Variable inputs, such as days fished, reflect the vessel utilisation level of the fixed inputs. The estimation of vessel capacity and capacity utilisation is undertaken using only fixed inputs, while technical efficiency involves the use of fixed and variable inputs. The available biomass is also an important input into production, but is considered a non-discretionary input. That is, the biomass or stock level is beyond the ability of the fisher to control. Biomass estimates can be directly incorporated into the production function specification of SFA models, but are more problematic in the case of DEA, requiring additional treatment due to their non-discretionary nature (Ruggiero 1998).

The drivers of efficiency can also be estimated. SFA can incorporate these directly in the production function or in the jointly estimated inefficiency equation (Battese and Coelli 1995). For DEA analysis, this is typically undertaken in a separate second-stage analysis. That is, the DEA calculations are conducted and the results for technical, allocative and other efficiency measures can then estimated as a function of the firm characteristics to determine which of these characteristics are associated with higher or lower levels of efficiency (e.g. Vestergaard et al. 2002, Tingley and Pascoe 2005, Hoff 2007, Chen et al. 2016, Scuderi and Chen 2019).

DEA has been identified as the most appropriate approach for estimating capacity and capacity utilisation in fisheries (Pascoe et al. 2003). DEA estimates of capacity utilisation have also been demonstrated to be consistent with those derived from economic data (e.g., cost functions) (Färe et al. 2000). While the 'raw' efficiency and capacity utilisation scores are affected by random variation,

[6] In practice, SFA generally estimates a flexible functional form such as a translog to serve as an approximation to a wide set of functional forms.

the derivation of unbiased capacity utilisation results (i.e., the ratio of the 'raw' technical efficiency to capacity utilisation scores) results in the effects of random noise being cancelled out (Holland and Lee 2002). As a consequence, the unbiased estimates of capacity utilisation are robust.

DEA and SFA can be calculated in standard statistical programs (e.g., R) or using specialised software (e.g., DEAP and Frontier[7]). The advantage of using a statistical program is that any required second-stage analysis can be performed directly. DEA and SFA use firm- or vessel-level data on individual (or subsets) of inputs and outputs.[8] When panel data are available, that is, multiple observations over time for each vessel, the statistical analysis is more consistent as unobserved characteristics can be controlled for. Vessel-level price and cost data are also desirable, particularly for deriving measures of allocative efficiency.

Species-specific biomass can also be incorporated as an input, although this can be challenging in multi-species fisheries (Andersen 2005, Pascoe et al. 2010, Pascoe et al. 2012). Excluding stock information can confound the estimation of technical efficiency, as changes in catch due to changes in stock conditions will manifest as efficiency change. However, 'assigning' a particular stock input to a particular output in multispecies models is not possible. For this reason, most DEA studies focusing on efficiency distributions compare only vessels operating in the same year, and in many cases the same area or métier (Tingley et al. 2005). This approach, however, precludes the assessment of changes in efficiency over time.[9] With single output SFA models, an aggregated stock index, or a series of dummy variables as a proxy for relative stock abundance, can be used (Andersen 2005).

The literature offers a large number of studies that use DEA (Pascoe et al. 2001, Dupont et al. 2002, Felthoven 2002, Tingley et al. 2003, Vestergaard et al. 2003, Tingley and Pascoe 2005, Walden 2006, Schrobback et al. 2015, Otumawu-Apreku and McWhinnie 2020) and SFA (Kirkley et al. 1995, Campbell and Hand 1998, Kirkley et al. 1998, Pascoe et al. 2001, Mardle et al. 2002, Fox et al. 2003, Squires et al. 2003, Kompas et al. 2004, Greenville et al. 2006, Pascoe et al. 2017, Scuderi and Chen 2019) and a small selection that use both (Tingley et al. 2003, Kirkley et al. 2004, Tingley et al. 2005).

In summary, DEA is preferred when there are multiple outputs and the focus of the analysis is measuring capacity and capacity utilisation. DEA is also more useful in measuring allocative efficiency (with multi-outputs) and scale efficiency.[10] However, as the technical efficiency component is subject to random error, SFA is preferred when a single (aggregate) output is appropriate and additional modelling of the marginal contributions of each input is of relevance (Pascoe and Tingley 2007).

Index number decomposition

Index number decomposition (IND) takes the simple CPUE structure of output divided by input but instead of specifying a single output and a single input, index number methods are used to calculate a disaggregated metric of outputs and inputs.

[7] The Centre for Efficiency and Productivity Analysis at the University of Queensland has several free packages available including DEAP and Frontier.

[8] Pascoe et al. (2016) 'experimented' with the use of spatial data (e.g., fishing grid) rather than individual vessels using DEA. The analysis was able to estimate changes in productivity over time of different parts of the fishery from a multispecies perspective.

[9] As will be seen in subsequent sections of the report, for the purposes of estimating changes in economic performance indicators (rather than efficiency distributions per se), the 'distortions' to the technical efficiency measures from excluding stock biomass measures may be beneficial. Increases in catch due to stock changes also result in higher revenues and improved economic performance.

[10] As these are also based on ratios, the random error component is also largely removed resulting in reliable estimates of these efficiency measures.

Index numbers measure changes in individual or aggregated measures over time, space or characteristic, relative to a base case. The base is typically normalized to one or 100, allowing direct interpretation of changes as percentages. The outputs and inputs can be specified as quantities or as values, which allows investigation of the contributions of changes in input and output prices as well as input and output quantities.

Using index number decomposition methods means that the output and input indexes can be disaggregated to whatever level data allows and the contribution of changes each to aggregate productivity or profitability can be determined and compared across time or vessels. The output measure may also take the form of vessel profitability, with profits being decomposed into price (input and output) and productivity impacts.

The type of index used include Malmquist (Walden et al. 2012), Törnqvist (Fox et al. 2006), Fisher (Stephan and Vieira 2013) and Lowe (Thunberg et al. 2015). Each allows the aggregate measure of output and the aggregate measure of input to be disaggregated to each of many outputs and inputs. The theoretical properties of each are slightly different so the basis for which is chosen depends on the circumstances. For instance, the Törnqvist index can be derived from a firm's profit maximization decision of a translog production function (Diewert 1976), so corresponds well to SFA analysis using translog production functions. Alternatively, the Lowe index is also theoretically robust but is computationally easy to construct so is well-suited for multi-fisheries analysis (O'Donnell 2012, Thunberg et al. 2015).

IND can be calculated in a spreadsheet or by using standard statistical programs (e.g., R or Stata). Like DEA and SFA, IND is effective for analysing behavioural responses when the data is detailed at the firm or vessel level. It can, however, be used on aggregate data to monitor aggregate trends across time. IND is useful to identify how differences in inputs and outputs contribute to differences in productivity or profitability and to track productivity or profitability over time.

Studies in the context of fisheries that have estimated IND include Fox et al. (2003), Dupont et al. (2005), Fox et al. (2006), McWhinnie (2006), and Ekerhovd and Gordon (2020). Australian examples of profit decomposition include Vieira (2011), Skirtun and Vieira (2012) and Pascoe et al. (2019).

Case Study Methodology

In many fisheries, the high cost of data collection relative to the value of the fishery limits the quantity and types of data that might be available to support fisheries management. Generally lowest in priority in the list of data to be collected is information on the economic performance of the fishery, as monitoring resource sustainability takes precedence. Basic catch and effort information, however, may contain implicit information about economic performance of the vessels. From these data, efficiency score and measures of capacity utilisation can be derived. The former can provide a proxy measure of the distribution of economic performance, while changes in capacity utilisation theoretically reflects changes in the economic conditions in the fishery.

Reflecting on the literature (as discussed in the 'Research gaps and discussion' section below) and considering the applicability of the key productivity measures to the Australian management context, we use a variety of approaches to estimate technical efficiency and capacity utilisation as benchmark performance metrics. We then compare these metrics to other economic metrics (e.g., gross margins, net profits) to assess the degree to which the productivity measures provide information on economic performance over time.

This multi-model approach for the case studies will allow us to outline: which metrics are possible to calculate from available data; in which data situations simple productivity measures are likely to be sufficient for effective decision making; and when more data intensive methods are likely to be required to inform effective decision making. An additional reason for conducting a parallel analysis is to be comparable with previous studies whilst highlighting the nuances in interpretation available from each approach. The primary focus is investigating the use of productivity analysis to provide consistent metrics of performance, but we also consider management change and biomass implications when relevant. While environmental changes are beyond the scope of our case studies, examples of previous studies, and other key questions of interest are provided as part of the review (as will be seen Table 1 in Results below). Determining the important components of productivity differences allows refinement of management to support effective economic outcomes in fisheries.

A simple schematic of the relationship between data, metrics of productivity and methods of analysis (as described in detail in previous sections) is shown in Figure 3. The Commonwealth Northern Prawn fishery acts as our benchmark case due to the availability of detailed economic information in addition to catch and effort data, which allows us to estimate all the productivity measures from different models. The South Australian Spencer Gulf and West Coast Prawn fishery has fewer observations available, so we use it to illustrate how different measures of output and performance contribute to a deeper understanding of a fishery. The Queensland Spanner Crab Fishery does not have economic information but the long history of catch data offers the opportunity to undertake a combined spatial and temporal analysis.

Data envelopment analysis

As identified in previous sections, the advantages of contemporary data envelopment analysis (DEA) include:

- A production function does not need to be specified in the estimation process, that is, it is non-parametric
- Random shocks to the production process outside the control of the fishers can now be incorporated through bootstrapping methods
- Vessel capacity and capacity utilisation can be estimated in a straightforward fashion by including only fixed inputs
- Technical efficiency can be estimated by including variable inputs
- Allocative efficiency can be estimated if value of outputs (e.g., fish prices), as well as quantity, measures are available
- Multiple outputs can be directly incorporated without having to aggregate a single measure of output
- Analysing drivers of efficiency through the use of a second-stage statistical analysis is possible
- Calculations can be performed in standard statistical programs (e.g., R), which allow any required second-stage analysis to be performed directly.

DEA methodology

We use DEA to assess the different productivity measures. DEA is well established in the economics literature for productivity analysis (Färe et al. 1989, Färe and Grosskopf 2000, Färe et al. 2000), and in fisheries in particular (Reid et al. 2003, Tingley et al. 2003, Vestergaard et al. 2003, Walden et al. 2003, Herrero 2005, Pascoe and Tingley 2006, Maravelias and Tsitsika 2008, Tsitsika et al. 2008). Stochastic production frontiers are often considered better at estimating technical efficiency in fisheries due to the often high degree of 'luck' involved in fishing,[11] particularly when efficiency is considered over a small time step (e.g., a day, week or month) (Lee and Holland 2000, Tingley et al. 2005). Over less frequent data (e.g., annual), however, short-term variations due to 'luck' may be averaged out. Studies

[11] Commercial fishing involves the pursuit and capture of an unseen fugitive resource. Fish movement is highly susceptible to short and long term environmental fluctuations, so fish may be in one spot one day and another place the next. While skipper skill is an important component of efficiency, and helps to reduce the impact of these environmental impacts (through better knowledge of both the environment and how fish respond), 'luck' remains an important factor affecting output in most fisheries e.g. Pascoe et al. (2002).

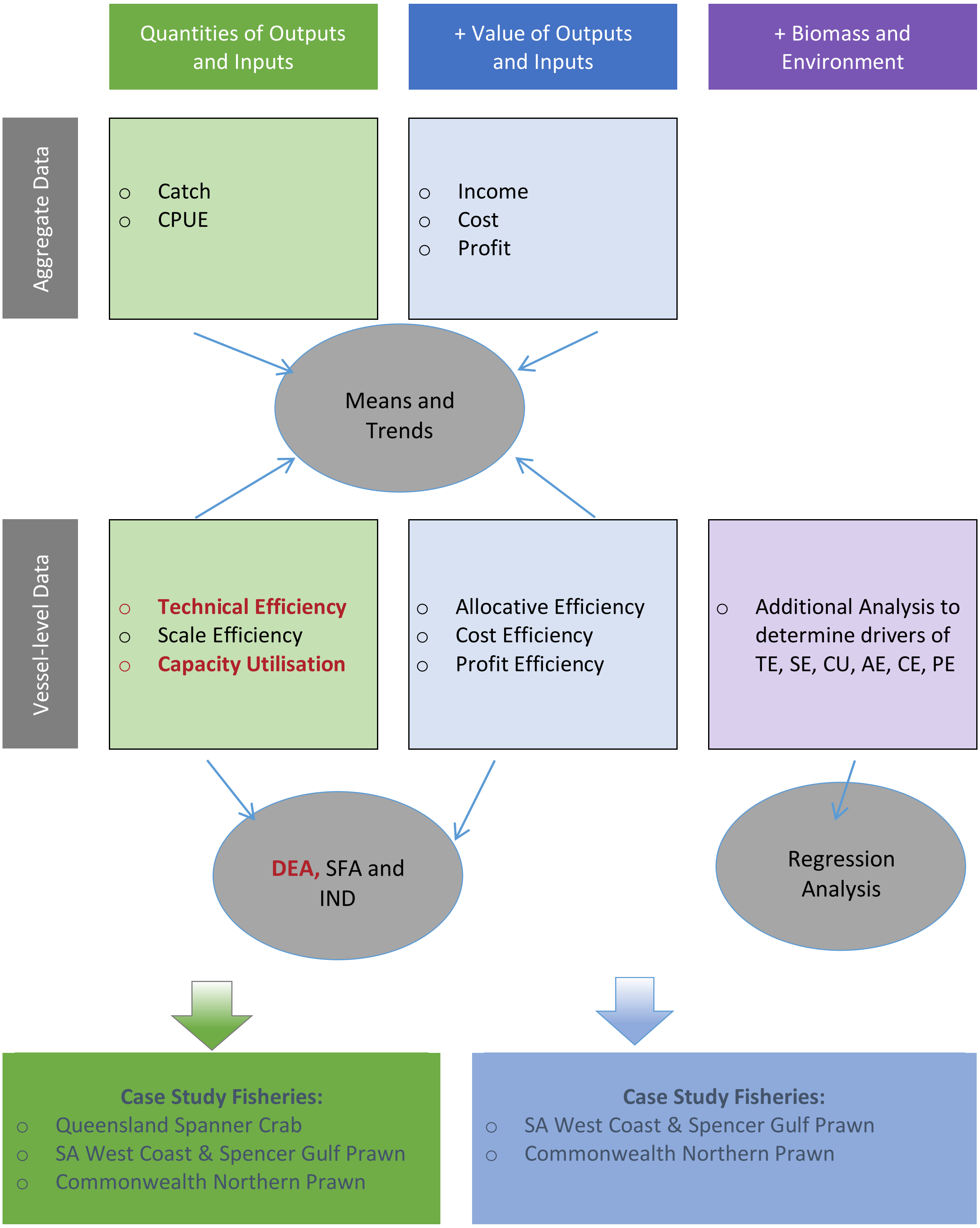


Figure 3. Data, methods and situation of case studies

Notes: The left-hand, green column, shows the possible metrics when quantity data is available, at aggregate or vessel level; the middle, blue column shows additional metrics when value data is also available; and the right-hand, purple column shows further possible analysis when appropriate biomass or environmental data is available. The grey ovals show the potential methods at each combination. The metrics (technical efficiency and capacity utilisation) and method (data envelopment analysis) used in all of our three case studies are in dark red, with our three case studies shown along the bottom.

applying DEA to panel data which is then averaged over the period of the data have been found to be less sensitive to stochastic error (Ruggiero 2007). DEA is generally considered as more appropriate for capacity estimation in multispecies fisheries (Färe et al. 2000, Pascoe et al. 2003, Tingley et al. 2003). Relatively few studies have considered allocative efficiency in fisheries (e.g. Esmaeili and Omrani 2007).

The general form of the output-oriented DEA model is given by:

$$Max\ \Phi_1 \tag{1}$$

subject to:

$$\Phi_1 y_{1,m} \leq \sum_j z_j y_{j,m} \quad m \in M \tag{2}$$

$$\sum_j z_j x_{j,n} \leq x_{1,n} \quad n \in N \tag{3}$$

where Φ_1 is a scalar showing by how much the production of each firm can increase output $y_{j,m}$ is amount of output *m* by boat *j*, $x_{j,n}$ is amount of input *n* used by boat *j* and z_j are weighting factors. The set of inputs (*N*) can be separated into fixed and variable factors. For capacity estimation, only fixed inputs are considered in the analysis (i.e., included in the set *N*), while technical efficiency estimation involves the inclusion of both fixed and variable inputs. Variable returns to scale can be imposed by adding a further restriction of $\sum_j z_j = 1$. Without this restriction, constant returns to scale are imposed.

The same model is used for both estimation of technical efficiency and capacity utilisation, the difference being the treatment of variable inputs. Capacity output is defined as Φ_1 multiplied by observed output (*u*), using fixed inputs only in the model. This also assumes that all inputs are used efficiently at their optimal capacity. Therefore, this measure represents the technically efficient capacity utilization (TECU), and is given by:

$$TECU = y \bullet (\Phi_1 y)^{-1} = \Phi_1^{-1} \quad . \tag{4}$$

The measure of TECU ranges from zero to 1, with 1 being full capacity utilization (i.e., 100 percent of capacity). Values less than 1 indicate that the firm is operating at less than its full output potential given the set of fixed inputs.

In practice, this measure reflects both technical efficiency and capacity utilisation. It is likely to be biased downwards as part of the increase in output may be due to improved efficiency as well as improved capacity utilisation (Färe et al. 1989). Hence, an adjustment is necessary to separate out the capacity utilisation component to correct for this bias. An adjusted or 'unbiased' estimate of capacity utilization can be estimated by:

$$CU = TECU \bullet TE^{-1} = \Phi_2 \bullet \Phi_1^{-1} \quad . \tag{5}$$

where Φ_2 represents the extent to which output can increase through using all inputs efficiently (i.e., including both fixed and variable inputs into the model analysis), and TE is the estimated level of technical efficiency, given by:

$$TE = \Phi_2^{-1} \tag{6}$$

This 'unbiased' measure also has other advantages. DEA is often criticised as a means of estimating efficiency as it does not account for random error. However, as any distorting effects of random error are similar (at least in terms of direction) in both Φ_1 and Φ_2, the ratio of the two is less affected by random noise (Holland and Lee 2002).

Productivity, expressed as total output per unit input, is greatest at the point where returns to scale are equal to 1 (Coelli et al. 1998). A measure of scale efficiency is estimated as the ratio of technical efficiency with variable returns to scale (i.e., $\sum z_j = 1$) compared with technical efficiency with constant returns to scale imposed (Coelli et al. 1998), which provides a measure as to how close a vessel is to the (technically) optimal scale (Orea 2002).

The final measure considered in the analysis was allocative efficiency. This is a measure as to the degree to which fishers are optimising their revenue given the relative prices of each output. The estimation of allocative efficiency requires first an estimation of the revenue efficiency, which is estimated as the revenue maximisation problem with variable returns to scale:

$$Max \sum_m p_m \varphi_1 y_{1,m} \tag{7}$$

subject to:

$$\varphi_1 y_{1,m} \le \sum_j z_j y_{j,m} \quad m \in M \tag{8}$$

$$\sum_j z_j x_{j,n} \le x_{1,n} \quad n \in N \tag{9}$$

$$\sum_j z_j = 1 \tag{10}$$

where φ represents the linear expansion factor to the revenue frontier. Revenue efficiency is given by $1/\varphi$, and allocative efficiency is determined ϕ_2/φ, or the ratio of revenue efficiency to technical efficiency. While not examined by Holland and Lee (2002) explicitly, it could be assumed that a similar outcome in terms of reduced influence of random variation on the performance measure would occur.

Second stage analysis

If additional information is available, a second stage analysis can also be undertaken to determine which of these factors may influence the relative productivity measures. Several previous studies have applied Tobit analysis to the resultant efficiency measures in order to determine which key factors influence performance (Dupont et al. 2002, Vestergaard et al. 2003, Tingley and Pascoe 2005, Tingley et al. 2005). This was on the basis that the productivity measures were limited to be between 0 and 1 and hence are censored at these levels. However, more recent analyses suggest that ordinary least squares (OLS) estimates may perform as well as (Hoff 2007), or better than Tobit analysis (McDonald 2009). McDonald (2009) suggests that DEA measures are not censored per se, but are instead normalised measures with a heteroskedastic disturbance, and hence Tobit may produce inconsistent estimates. Instead, McDonald (2009) suggests the use of OLS with correction of the standard errors for heterosckedasticity as a more appropriate approach.

Stochastic production frontier analysis

Stochastic production frontiers are econometric models that estimate the output of a vessel as a function of a number of inputs (fixed and variable) as well as a measure of the relative inefficiency of the vessel. As identified in the earlier methodologies section, the advantages of stochastic production frontier analysis (SFA) over DEA include:

- Random error (e.g., stochastic variations in stock abundance, or 'luck') can be separated from technical efficiency
- The drivers of efficiency can be estimated in a one-step process by incorporating these directly in the production function or in the jointly estimated inefficiency equation (in DEA a separate second-stage analysis is required)

- Parameters of the production function represent production elasticities, of additional use to management in understanding the effects of changes in inputs on outputs

SFA have been applied in a wide range of fisheries internationally (Kirkley et al. 1995, Pascoe et al. 2001, Pascoe and Coglan 2002, Zen et al. 2002, Herrero and Pascoe 2003, Squires et al. 2003, Tingley et al. 2005) as well as a range of fisheries in Australia (Kompas et al. 2004, Greenville et al. 2006, Pascoe et al. 2013, Pascoe et al. 2017, Pascoe et al. 2018). In the northern prawn fishery, the approach has been used to assess technical efficiency in the tiger prawn fishery (Pascoe et al. 2012) as well as the banana prawn fishery (Kompas et al. 2004).

SFA methodology

A number of different functional forms for the production frontier exist, although the most flexible is the translog production frontier (Aigner et al. 1977, Meeusen and Van den Broeck 1977), given by:

$$\ln y_i = \beta_0 + \sum_k \beta_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} - u_i + \varepsilon_i \qquad (11)$$

where *y* is the quantity of output produced, *x* is a vector of inputs, *u* is a one-sided error term $(u \geq 0)$ representing the level of inefficiency of the vessel and ε is a random error term. The technical efficiency (TE) of the i-*th* vessel, is given by $TE_i = exp\ (-u_i)$.

In order to separate the stochastic and inefficiency effects in the model, a distributional assumption about the inefficiency term has to be made. Commonly, both a half normal and truncated normal distribution is tested (Battese and Coelli 1988), along with the potential for time variant efficiency (Cornwell et al. 1990). Following Battese and Coelli (1995), the drivers of inefficiency can be also estimated through an explicit inefficiency model, given by

$$u_i = \sum_m \delta_m z_{i,m} + \varpi_i \qquad (12)$$

where $z_{i,m}$ is the vessel specific characteristic assumed associated with inefficiency and ϖ_i is a random variable.

Capacity utilisation can be estimated in a similar way to technical efficiency, including fixed inputs only into the production function (Kirkley et al. 2004). However, as with the DEA approach, this measure captures both capacity utilisation and technical efficiency. Potentially, as will be examined in this study, an unbiased measure of capacity utilisation could be derived by dividing capacity utilisation by technical efficiency.

For profit maximisation, economic theory requires that the translog production function be monotonically increasing (i.e., $\partial y_i / \partial x_i \geq 0 \ \ \forall\, i,x$), and quasi-concave for all inputs (Lau 1978, Sauer and Hockmann 2005, Sauer 2006, Sauer et al. 2006). Henningsen and Henning (2009) developed a method to test these assumptions and, where necessary, impose monotonicity conditions in the model combining parametric and non-parametric estimation of the model coefficients. This involves first estimating the stochastic translog production frontier and extracting the unrestricted parameters $\hat{\beta}$ and their covariance matrix $\hat{\Sigma}_\beta$. Second, we estimate restricted $\hat{\beta}^o$ parameters using a minimum distance approach, given by:

$$\hat{\beta}^o = \text{argmin}\left(\hat{\beta}^o - \hat{\beta}\right) \hat{\Sigma}_\beta^{-1} \left(\hat{\beta}^o - \hat{\beta}\right) \qquad (13)$$

subject to:

$$\frac{\partial f(x,\beta^{o})}{\partial x} \geq 0 \quad \forall i,x \qquad (14)$$

This is solved using quadratic programming to find the revised set of coefficients $\hat{\beta}^{o}$ that conform to the monotonicity assumption. Finally, the stochastic frontier model is re-estimated as:

$$\ln y_i = \alpha_0 + \alpha_1 \ln \tilde{y} - v_i + \varepsilon_i \qquad (15)$$

where $\tilde{y} = f(x,\hat{\beta}^{o})$. That is, the only input is the estimated frontier output based on the restricted parameters. The parameters α_0 and α_1 represent final adjustments to the parameter estimates. An advantage of the three-stage approach is that the parameter values estimated in the first stage provide appropriate starting values while the variance-covariance matrix limits the degree to which these parameters are altered when imposing monotonicity in the non-parametric component. While not imposed, convexity is tested *ex post*. (Henningsen and Henning 2009) argue that there is less need to impose the convexity constraints when estimating production frontiers as these are based on the assumption that producers aim to maximise output for a given set of inputs rather than profit maximisation *per se*, and suggest that only monotonicity be imposed.

Stochastic multi-output distance function

A further alternative modelling approach is the estimation of a stochastic multi-output distance function. As a multi-output model, it is analogous to DEA in that it estimates a multi-output frontier with the efficiency score based on the distance to the frontier through a radial expansion. The model has the advantage in that it does not require aggregation of the outputs, avoiding some of the limitations of the previous stochastic production frontiers which require a single aggregated output measure. As it is a parametric modelling approach, it also can account for random variation in the estimation of inefficiency. Multi-output distance functions have been applied in a range of international (Fousekis 2002, Orea et al. 2005, Pascoe et al. 2007) and Australian (Pascoe et al. 2010, O'Donnell 2012, Pascoe et al. 2012) fisheries.

The translog distance function with *M* (*m = 1, 2, …, M*) outputs *Y*; *K* (*k = 1, 2, …, K*) inputs *X*; and for *I (I = 1, 2, …, I)* firms can be given by:

$$\begin{aligned}\ln D_i = \beta_0 &+ \sum_m \beta_m \ln y_{m,i} + 0.5 \sum_m \sum_n \beta_{m,n} \ln y_{m,i} \ln y_{n,i} \\ &+ \sum_k \beta_k \ln x_{k.i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\ &+ \sum_k \sum_m \beta m \ln x_{k,i} \ln y_{m,i} + v_i\end{aligned} \qquad (16)$$

where D_i is the direction distance functional value representing the distance from the production possibility frontier $(0 \leq D_i \leq 1)$, $y_{m,I}$ and $x_{k,I}$ are the outputs and inputs used by vessel I, and v_i is a stochastic error term. The output distance function is homogeneous of degree one in outputs (Shephard 1970). Homogeneity can be imposed through normalizing the function by one of the outputs, and rearranging the model such that:

$$
\begin{aligned}
-\ln y_{1,i} = \beta_0 + \sum_{m\neq 1} \beta_m \ln y^*_{m,i} + 0.5 \sum_{m\neq 1}\sum_{n\neq 1} \beta_{m,n} \ln y^*_{m,i} \ln y^*_{n,i} \\
+\sum_k \beta_k \ln x_{k.i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\
+\sum_k \sum_m \beta m \ln x_{k,i} \ln y^*_{m,i} + v_i - \ln D_i
\end{aligned} \tag{17}
$$

where $y^*_{m,i} = y_{m,i} / y_{1,i}$ and the distance measure is equivalent to the inefficiency term in the single output production frontier (i.e., $u_i = lnD_i$). The distance function can be transformed into a more traditional production frontier by reversing the sign of the dependent variable. While not critical in this application, the 'missing' coefficients from the model can be derived though the homogeneity conditions $\sum_m \beta_m = 1, \sum_n \beta_{m,n} = \sum_m \beta_{k,m} = 0$. As with the single output stochastic production frontier, assumptions need to be made as to the distribution of the inefficiency term in order to separate out the random component from inefficiency.

Decomposition of technical change and efficiency change over time (Malmquist Index)

When price and cost data are not readily available, or when it is not optimal to assume that the firms in question are cost minimisers or revenue maximisers, the Malmquist index is the appropriate choice (Hoff 2006). This approach has the additional benefit that it can be divided into a component describing the efficiency change and a component describing the technological change (e.g., due to technological progress) of the firms (Färe et al. 1998).

Malmquist Index can be decomposed into technical change (TC) and efficiency change (EC) using distances measured relative to DEA frontiers (Färe et al. 2011). The performance of firm *i* in period *s* against the technology in period *t* can be written as:

$$TC(s,t) = \sqrt{\frac{E(t,s)E(s,s)}{E(t,t)E(s,t)}} \tag{18}$$

$$EC(s,t) = \frac{E(t,t)}{E(s,s)} \tag{19}$$

$$M(s,t) = \sqrt{\frac{E(t,s)E(s,s)}{E(t,t)E(s,t)}}\frac{E(t,t)}{E(s,s)} = TC(s,t)EC(s,t) \tag{20}$$

where *TC(s,t)* is the technical change between period s and t, *EC(s,t)* is efficiency change between period s and t, and *M(s,t)* is the corresponding derived Malmquist index. The *TC* values above 1 represent technological progress in the sense that more can be produced using fewer resources. The EC and TC effects are multiplicative, such that $TC * EC = M$. If the production technology exhibits constant returns to scale (CRS) then there are only two sources of productivity growth: efficiency change and technical change (Coelli et al. 2005). However, if the production technology exhibits variable returns to scale (VRS) there are two other sources of productivity growth: improvement in scale efficiency and variations in the output-mix and the input-mix (Coelli et al. 2005).

The Malmquist index is estimated using a variant of DEA, where E(s,s) (analogously E(t,t)) is given by:

$$E_1(s,s) = 1/(Max\,\Phi_1) \tag{21}$$

subject to:

$$\Phi_1 y^s_{1,m} \leq \sum_j z_y y^s_{j,m} \quad m \in M \tag{22}$$

$$\sum_j z_j x^s_{j,n} \leq x^s_{1,n} \quad n \in N \tag{23}$$

and E(t,s) is given by:

$$E_1(t,s) = 1/(Max\,\theta_1) \tag{24}$$

subject to:

$$\theta_1 y^t_{1,m} \le \sum_j z_y y^s_{j,m} \quad m \in M \tag{25}$$

$$\sum_j z_j x^s_{j,n} \le x^t_{1,n} \quad n \in N \tag{26}$$

where *s* and *t* are consecutive years. That is, the output in year t (using inputs in year t) is compared with the output and inputs from year s.

Examples of studies where the Malmquist index has been constructed to study productivity changes for fishing fleets include work by Hoff (2006) on a North Sea purse seine fleet, and Oliveira et al. (2009), who constructed the Malmquist index for an artisanal fishing fleet in Portugal. Walden et al. (2012) examined productivity change in the Mid-Atlantic surf clam and ocean quahog fishery and showed that although overall productivity declined after the introduction of individual transferable quota (ITQ), technical change increased post-ITQ rapidly, and did not decline in subsequent years. The Malmquist index was also used by Herrero and Pascoe (2004) in order to calculate a stock index based on the changes in the DEA efficiency scores over time, and used to estimate banana prawn biomass for subsequent use in an SFA by Pascoe et al. (2018).

Using the Northern Prawn Fishery data, firm level productivity changes in the form of Malmquist Index (M), technical change index (TC), and efficiency change index (EC) between 1999 and 2019 were calculated using the Malmquist function in Benchmarking package in R, with 1999 as a base year (M=TC=EC=1).

R statistical software

The project team identified that using R (R Core Team 2021) would be the most practical approach for analysis as it is free, widely used, and has effective packages available for DEA, SPF and statistical analysis. This means that the case studies can use consistent methodology and can be undertaken by different team members to retain confidentiality of data.

Results and Discussion

This section is in four parts: firstly, the Review of Productivity and Efficiency Analysis in Fisheries, including the associated compendium of examples; and subsequently, the productivity analyses for each of the case studies – Commonwealth Northern Prawn Fishery, South Australian Spencer Gulf and West Coast Prawn Fisheries, and Queensland Spanner Crab Fishery.

Review of Productivity and Efficiency Analysis in Fisheries

Themes within the broader literature

To assess broader themes and trends in the extant literature within the field of productivity and efficiency analysis of fisheries, an assessment of key authors and important publications, important keywords and terms in abstracts of publications was undertaken using the VOSViewer software.

We used 256 relevant publications that were derived from the Web of Science database and their bibliometric datasets (e.g., keywords, abstracts) to identify important words/terms and co-occurrence of the words used. This was done using keyword listing for each publication and for words or terms in the abstracts. An analysis of titles was not undertaken as abstracts typically offer more comprehensive information about the content of a publication.

The results are presented using the VOSViewer visualisation maps. Each point in the network map signifies an item (e.g., keyword or term); larger points indicate items with a higher weight that are regarded as more important than an item with a lower weight. The links show which items co-occur with each other in a given publication. The clusters are determined by the software and are non-overlapping, implying that each item can only belong to one cluster.

Figure 4 shows four main clusters of keywords: efficiency, input, output, index numbers, capacity (yellow); management, behaviour (green); DEA, productivity (red); and technical efficiency, stochastic production frontier (blue). As noted in the previous section, SFA is also referred to by multiple names, whereas data envelopment analysis has a single, common name. This means that the term 'data envelopment analysis' occurs more prominently as a single (red) dot in the figure compared to the terms 'stochastic production frontier', 'stochastic frontier', 'frontier productions function', which together form the blue network. Index numbers appear in a different, less connected cluster (yellow) within the literature.

Figure 5 depicts a map of term occurrence based on binary counting of a term in the abstract of documents. Binary counting means that only the presence or the absence of a term in a document matter. The number of occurrences of a term in a document is not taken into account. The major themes within the document abstracts include: technical efficiency and determinants influencing technical efficiency, e.g., firm, age, farmer, experience (red); data envelopment analysis (blue); and management aspects of vessels, fleets and species, e.g., quota, catch, effort, regulation (green).

The identified themes in the abstracts of documents (Figure 5) and the keyword themes (Figure 4) share some common elements (technical efficiency, data envelopment analysis and management are prominent in both), yet the abstracts appear to include more active terms (e.g. change, growth, implementation) while the keywords include more methods and applications (e.g. DEA, frontier, rights, industry).

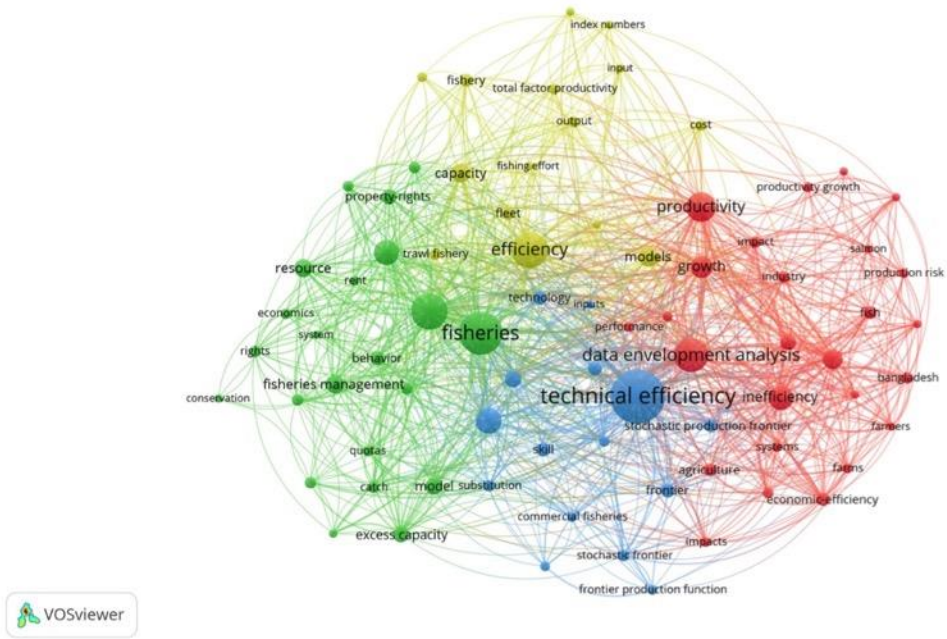


Figure 4. Identified themes based on occurrence of keywords

Notes: Keywords includes author keywords and KeyWords Plus. A minimum number of 5 occurrences of a term was used as a threshold. Of 1039 keywords, 78 met this threshold. For each of the 78 terms, a relevance score was automatically calculated by the software. Based on this score, the most relevant terms were selected. The default choice is to select the 60% most relevant terms.

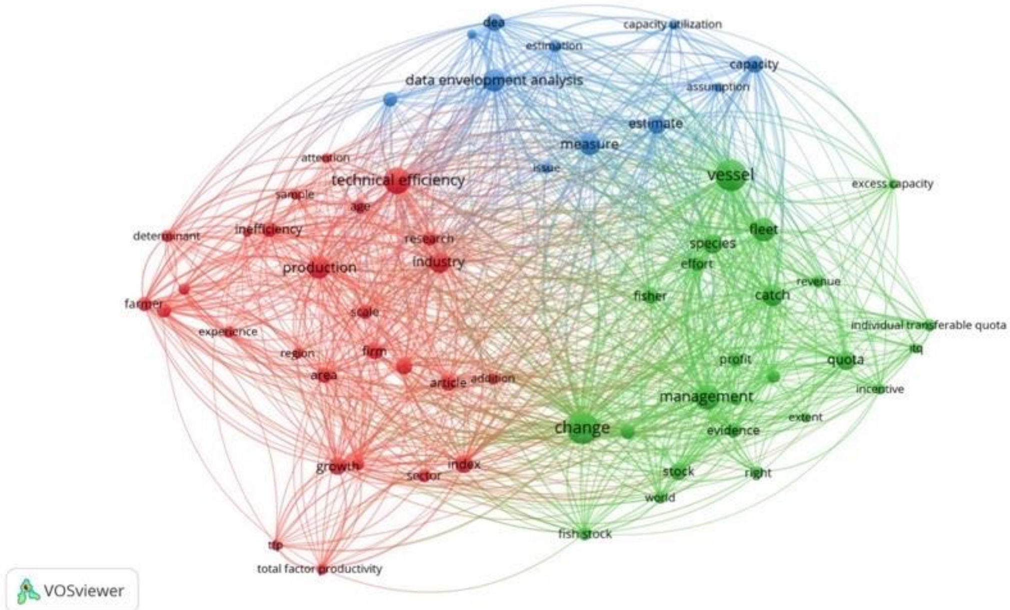


Figure 5. Identified themes based on occurrence in abstract text

Notes: A minimum number of 10 occurrences of a term was used as a threshold. Of 4691 terms, 104 terms met this threshold. For each of the 104 terms, a relevance score was automatically calculated by the software. Based on this score, the most relevant terms were selected. The default choice is to select the 60% most relevant terms. Subsequently, 62 terms were selected.

Significant contributions to the field of research

In addition to major themes identified within the literature, our assessment also focussed on identifying prominent authors and research outlets, and important publications in the field.

Figure 6 shows important authors by the number of documents within the 256 observations. The threshold criterion was that authors had to have at least 5 publications. Fourteen authors qualified under this creation. Figure 6 illustrates four main clusters: Pascoe, Tingley, Coglan, Punt (green); Squires, Kirkley, Felthoven, Walden, Jeon (red); Asche, Roll, Tveteras (blue); and Vestergaard (yellow).

Figure 7 offers a visualisation of citations by source. Marine Policy, Marine Resource Economics, Aquaculture Economics and Management and Fisheries Research are the journals with the highest number of citations in this field of research. This emphasizes the importance of these journals in disseminating methods and results in this area and why they are the 'go to' jounals. The distance between two journals in the visualization indicates the relatedness of the journals in terms of co-citation links. In general, the closer two journals are located to each other, the stronger their relatedness. The strongest co-citation links between journals are represented by the lines.

Figure 8 illustrates how the productivity and efficiency in fisheries and aquaculture literature draws upon one another by depicting the results for the number and co-occurrence of citations. While some of the most cited articles in the international literature in this field of research focus on methodological advancements (Battese et al. 2004, Hoff 2007), other publications centre around the importance of productivity assessment in fishery management (Squires 1987, Arnason 1990, Smith et al. 1999, Asche et al. 2013, Costello et al. 2016) or offer early case studies which apply the method (Kirkley et al. 1995, Kirkley et al. 2002). The most important individual contributions are Smith et al. (1999), Battese et al. (2004), Hoff (2007) and Costello et al. (2016).

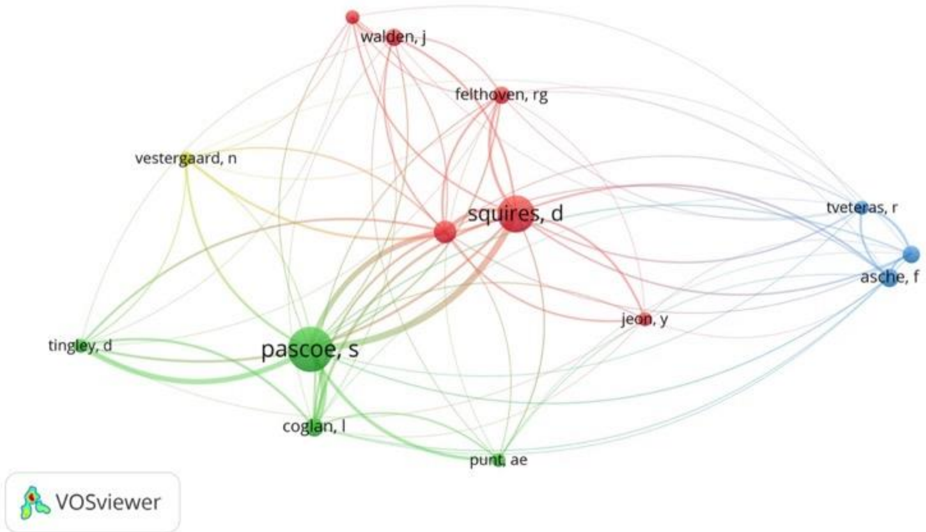


Figure 6. Important authors and citation links between them

Notes: A minimum number of 5 occurrences of a term was used as a threshold. Of 474 authors, 14 met this threshold. For each of the 14 authors, the total strength of the citation links with other authors was automatically calculated by the software. The authors with the greatest total links were selected. Subsequently, 14 terms were selected.

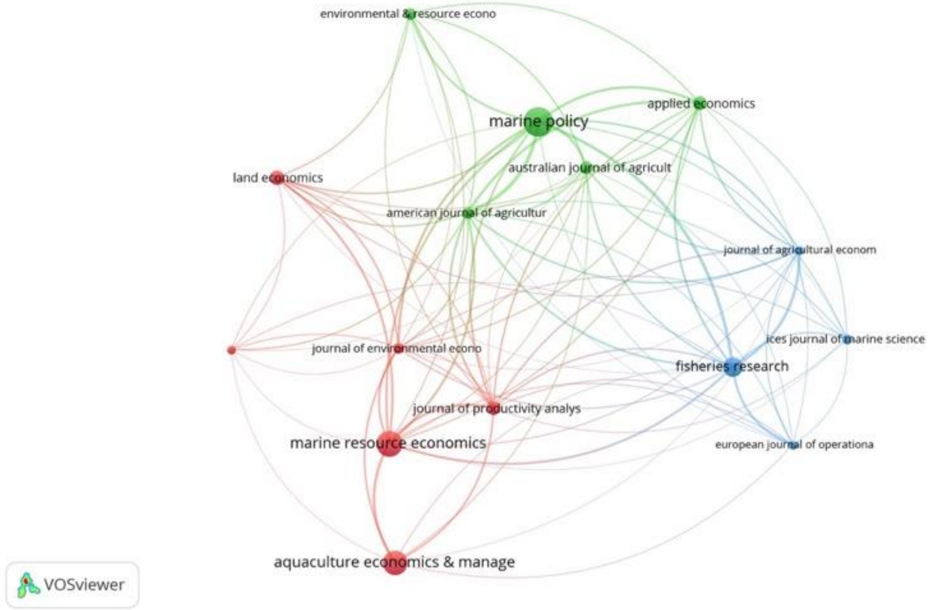


Figure 7. Key journal outlets and citation links between them

Notes: A minimum number of 5 occurrences of documents published in each journal was used as a threshold. Of 76 sources, 15 met this threshold. For each of the 15 journals, the total strength of the citation links with other sources was automatically calculated by the software. The sources with the greatest total links were selected. Subsequently, 15 terms were selected.

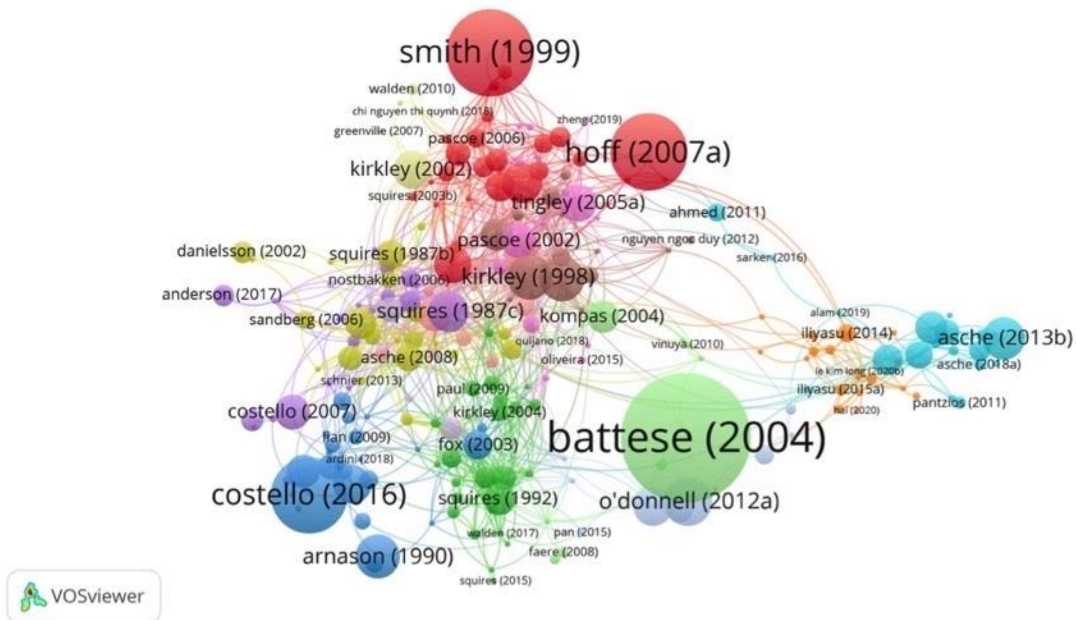


Figure 8. Important works and co-occurrence of citation

Notes: A minimum number of 0 citations of a document was used as a threshold. Of 256 documents, 256 met the threshold. For each of the 256 terms, the number of citation links was automatically calculated. Documents with the largest number of links were selected. The largest set of connected items consisted of 234 items.

Smith et al. (1999) is not a productivity analysis paper but it is referenced as it describes how management strategy evaluation (MSE) can be used to clarify multiple management objectives and trade-offs and outlines the limitations using AFMA fisheries. Its conclusions that fisheries need stable management and regulation with clear objectives and monitoring, long-run incentives for industry, and low chance of political uncertainty, remain relevant.

Battese et al. (2004) is a good example of a paper outside of fisheries that has had considerable influence due to the method being of particular relevance to fisheries analysis. It develops a metafrontier SFA model for an industry with subgroups to allow technical efficiency to be divided into parts compared to both the subgroup and to the metafrontier.

Hoff (2007) is a methodological contribution in fisheries analysis that compares alternative methods for estimating the second-stage regressions in a DEA. The Danish case study provides a clear context and reminds us that all models will be misspecified in some way so results should be interpreted accordingly.

Costello et al. (2016) estimates bioeconomic models in 4713 fisheries worldwide by calculating business-as-usual, maximum sustainable yield and rights-based management outcomes for each. They find that business-as-usual will lead to greater stock divergence while sound management could increase catch and profit. This comprehensive study is a nice example of taking a consistent approach across many fisheries, but with limited detail for each.

Trends and developments within the broader literature

Early empirical work tended to use aggregate data, e.g., Norton et al. (1985) Squires (1994), and this has continued to be used to identify overall trends in ratios of outputs to inputs for individual or groups of fisheries. In the 1990s and 2000s, methodology of productivity analysis was developed and applied to fisheries purposes to estimate technical efficiency, performance and productivity and gain a deeper understanding of these in different fisheries.

The FAO Technical Working Group on the Management of Fishing Capacity (1998) and related work (Vestergaard et al. 2002, Pascoe et al. 2003, Squires et al. 2003) formed a clear and consistent agenda for using DEA to estimate capacity and capacity utilisation. The objective of this work was to assist fisheries managers to address and prevent overcapacity. In doing so, the development and application of consistent metrics across fisheries was undertaken. This lead to a focus on DEA methods, both in terms of improving the methodology and in application to fisheries, in the subsequent decade (Morrison Paul et al. 2010).

The advantage of using a consistent methodology is particularly important when multiple fisheries are managed under the same policy, such as the EU Common Fisheries Policy or the Australian Commonwealth Fisheries Harvest Strategy Policy. There are relatively few studies that systematically study multiple fisheries in a single document: Norton et al. (1985) calculated indexes for prices, costs and effort in eight key US fisheries; Vestergaard et al. (2002) uses the FAO (1998) DEA methodology to analyse fisheries in six EU countries; Skirtun and Vieira (2012) decomposes Törnqvist indexes to determine drivers of profitability in Australian Commonwealth fisheries; Stephan and Vieira (2013) uses Fisher indexes to measure TFP in the Commonwealth fisheries; and Thunberg et al. (2015) estimates productivity change for 20 catch share fisheries in the US using a Lowe index.

While consistent methodology is valuable, so too is the development and application of improved methods. As described in Productivity Measures and Methodologies, SFA and DEA can both be used to estimate efficiency: SFA tended to be used to account for stochastic changes in catch, while DEA was applied more in cases of multiple outputs. The literature has, however, progressed from measuring efficiency to determining why efficiency has changed. SFA has the advantage in this space as it allows jointly estimating efficiency and the determinants, which is more statistically robust (Oliveira et al. 2016). To estimate the determinants of efficiency using DEA requires a second, separate step of specifying a regression model (Vestergaard et al. 2002, Tingley et al. 2005).

In addition to the improvement in methods, the literature has also evolved to address questions beyond the direct measurement of efficiency to asking questions regarding why and how. This was foreshadowed in an early review of the literature by Felthoven and Morrison Paul (2004) who discussed the future need to incorporate by-catch (subsequently addressed by Färe et al. (2011) and Färe et al. (2006)), environmental conditions (see Chen et al. (2016)), management effects (Fox et al. 2006, Pascoe et al. 2011, O'Donnell 2012, Pascoe et al. 2012, Walden et al. 2012, Pascoe et al. 2013, Zhou et al. 2013, Thunberg et al. 2015, Rust et al. 2017, Scheld and Walden 2018, Ekerhovd and Gordon 2020, Otumawu-Apreku and McWhinnie 2020), and multi-species (e.g. Andersen (2005), Herrero et al. (2006), Pascoe et al. (2007) and Felthoven et al. (2009)).

The literature is also drawing from trends in the wider economics literature. For instance, Grifell-Tatjé et al. (2018) urge researchers to consider dispersion, heterogeneity, inequality, and the impact of institutions, which Chen et al. (2016) does for quantiles of environmental changes and Grainger and Costello (2016) consider the implications of firm heterogeneity when moving to a rights-based fishery. Other work, such as Reimer et al. (2017), Reimer et al. (2017), Scheld and Walden (2018), acknowledges that the revealed production possibilities are frequently constrained and confounded by regulatory incentives so estimating underlying technological and behavioural parameters in structural models to conduct ex ante policy analysis is needed.

We can assess the change in themes in the bibliometric analysis of the literature by splitting the sample in two, based on the median publication year. Figure 9 shows the results for occurrences of terms in abstracts for the sub-sample covering the period 1987-2013, and Figure 10 covers 2014-2020. Each uses the same threshold of a minimum of 10 occurrences for a term but the map in the early period is much sparser and is largely methodological terms such as productivity, performance, efficiency and DEA.

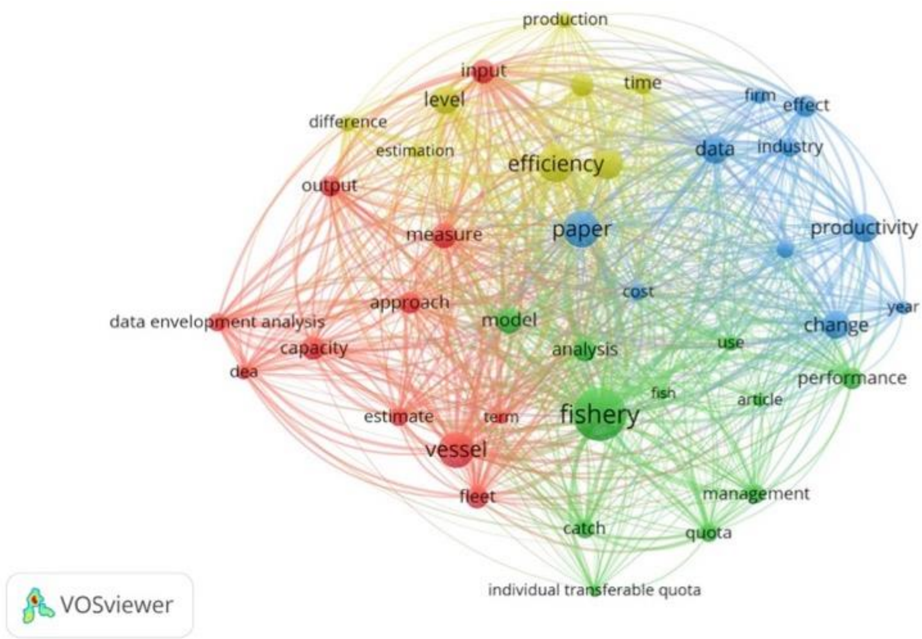


Figure 9. Identified themes based on co-occurrence in abstract text 1987-2013

Notes: A minimum number of 10 occurrences of a term was used as a threshold. Of 2231 terms, 40 terms met this threshold. For each of the 40 terms, a relevance score was automatically calculated by the software. Based on this score, the most relevant terms were selected. The default choice is to select the 60% most relevant terms. Subsequently, 40 terms were selected.

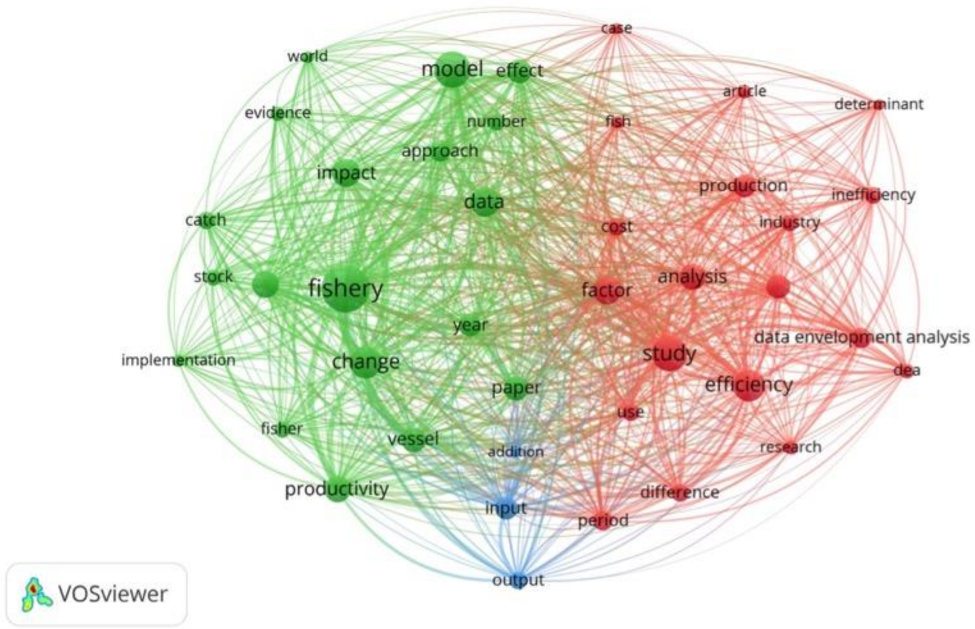


Figure 10. Identified themes based on co-occurrence in abstract text 2014-2020

Notes: A minimum number of 10 occurrences of a term was used as a threshold. Of 3040 terms, 41 terms met this threshold. For each of the 41 terms, a relevance score was automatically calculated by the software. Based on this score, the most relevant terms were selected. The default choice is to select the 60% most relevant terms. Subsequently, 41 terms were selected.

Prior to 2014 (Figure 9), four clusters of themes in the abstracts can be observed: fishery management and performance (green); DEA, capacity, approach, measure (red); efficiency and production (yellow); and data, change, productivity (blue). After 2013 (Figure 10) the terms in abstracts appear to be more clearly categorised into: efficiency, analysis and DEA (red); and fishery, management, impact and change (in green), representing the evolution towards applications seeking to understand management and environmental changes and impacts. A final, smaller cluster around input and output was identified (blue).

Themes within the Australian literature

The literature of efficiency and productivity analysis of Australian fisheries is relatively limited in size. 28 publications were identified: three are reports; ten are conference or working papers; and 15 are published in academic journals. Table 17 in Appendix B. Compendium of Examples of Economic Productivity Analysis in Fisheries provides a summary of the Question, Fishery, Period, Data, Management, Method and Conclusion for each.

As can be seen from the references to examples of methods in Productivity Measures and Methodologies, the Australian literature has used a variety of productivity methods. For data envelopment analysis: Otumawu-Apreku and McWhinnie (2021), Pascoe et al. (2013), Schrobback et al. (2015), Rust et al. (2017), Otumawu-Apreku and McWhinnie (2020). For stochastic frontier analysis: Kompas et al. (2004), Kompas and Che (2005), Greenville et al. (2006), Pascoe et al. (2010), Pascoe et al. (2011), New (2012), O'Donnell (2012), Pascoe et al. (2012), Pascoe et al. (2013), Green (2016), Pascoe et al. (2017), Pascoe et al. (2018). And for index number decompositions: Fox et al. (2006), Perks et al. (2011), Vieira (2011), Skirtun and Vieira (2012), Skirtun (2013), Stephan (2013), Stephan and Vieira (2013), Pascoe et al. (2019).

The Commonwealth fisheries have been analysed individually (Kompas et al. 2004, Kompas and Che 2005, Fox et al. 2006, Pascoe et al. 2010, Pascoe et al. 2011, New 2012, O'Donnell 2012, Pascoe et al. 2012, Pascoe et al. 2013) and within systematic analyses (Perks et al. 2011, Skirtun and Vieira 2012, Skirtun 2013, Stephan 2013, Stephan and Vieira 2013). The Commonwealth fisheries have the most detailed data, which allows use of the most sophisticated methods of analysis. Several State fisheries have been studied; these are the higher valued fisheries of rock lobster, oysters and prawns (Greenville et al. 2006, Schrobback et al. 2015, Pascoe et al. 2017, Rust et al. 2017, Pascoe et al. 2019, Otumawu-Apreku and McWhinnie 2020, Otumawu-Apreku and McWhinnie 2021).

The Australian literature is generally focussed on characterising efficiency and productivity in each of the case study fisheries. There is a strong theme of analysing the impact of management change, for instance the moves to individual transferable quotas (Pascoe et al. 2010, Pascoe et al. 2011, New 2012, Pascoe et al. 2012, Skirtun and Vieira 2012, Stephan and Vieira 2013, Rust et al. 2017, Otumawu-Apreku and McWhinnie 2020) and buybacks (Fox et al. 2006, Skirtun and Vieira 2012, Pascoe et al. 2013, Skirtun 2013). As with the wider literature, including the effects of biomass (Fox et al. 2006, Skirtun and Vieira 2012, Stephan and Vieira 2013), and, more recently, environmental conditions (Schrobback et al. 2015) and distributional implications (Pascoe et al. 2013, Green 2016) have been considered.

Compendium of examples of economic productivity analysis in fisheries

The assessment of the literature also elicited the type of questions addressed by the reviewed studies. For the purpose of this compendium, we present three tables that summarise the literature in two ways. Table 1 provides an overview of the key questions identified and examples of the methods and applications. Table 17 in Appendix B presents summaries of each of the Australian studies, and any international studies from Table 1 are summarized in Table 18. These alternative tabulations allow readers to identify relevant examples by the type of question, time period, type of data, method of analysis, management type, and location. Table 17 is particularly useful for Australian managers to see what questions have been addressed and how within the Australian context.

As the references in Table 17 and Table 18 are published resources, we do not replicate them in a document but have provided the official Digital Object Identifier (DOI) for each. For readers without access to academic journals via a government or university library, we have also, where possible, provided a Uniform Resource Locator (URL) for a pre-print or working paper version.

Research gaps and discussion

This review has identified that determining what the aggregate levels and trends in productivity for a fishery can be achieved with commonly available data and straightforward methods. Determining why these levels and trends manifest and how they might change if either variable or exogenous inputs change, requires more information and different methodologies.

For single fisheries with high value, complex needs, central governance, and management changes (e.g., the Commonwealth Northern Prawn Fishery, see Table 17) the need for and ability to collect detailed data is high and has been analysed with a variety of methodologies to address a range of questions. For the few studies that have considered multiple fisheries together using a consistent methodology (e.g., the Commonwealth fisheries or the US or EU fisheries, see Themes within the broader literature), the analysis is constrained by the level of data in the least-data fishery. One solution would be to move towards more data collection across all fisheries. However, while the ease of collecting data is improving, it is not costless. An alternative solution is to heed the advice of Prager and Williams (2003) to determine how much better the management based on full data is compared to limited data. Gaining information about the consistency of productivity indicators when we apply different methods of analysis is important as this would allow smarter use of the data and methods.

Table 1. Key questions and examples of methods and applications

How is catch, revenue, cost or profit changing over time?	
IND of TFP of quantities	O'Donnell (2012) Northern Prawn Fishery 1974-2010 with Bayesian methods for small sample and multiple outputs
IND of quantities	Stephan and Vieira (2013) Commonwealth fisheries 1990/94-2010/11
DEA multi-output revenue	Schrobback et al. (2015) Moreton Bay Oyster 1997-2012
TFP including biomass	Jin et al. (2002) New England groundfish 1964-1993
Is this because the quantity or the quality of inputs or outputs has changed?	
IND of profit	Fox et al. (2003) Pacific halibut 1988-1994
SFA of cost	Sandberg (2006) Norwegian herring and cod 1990-2000
How does management affect outcomes?	
SFA of costs	Asche et al. (2008) IQ for five EU cod 1997-2001
IND of profits	Ekerhovd and Gordon (2020) Norwegian purse seine 1994-2013 and IQs
DEA of profits	Otumawu-Apreku and McWhinnie (2020) of IQ for SA lobster 1997-2008
Is this because biomass or the environment has changed?	
IND with and without biomass adjustment	Thunberg et al. (2015) 20 US fisheries 1987-2010
DEA with second-stage regression	Chen et al. (2016) Connecticut lobster 1998-2007 with changes in ambient water quality
What is the capacity and capacity utilization of the fleet?	
DEA with second-stage regressions to calculate CU and TE	Vestergaard et al. (2002) numerous EU fisheries 1990s with consistent FAO method and definitions
DEA and SFA of output to calculate CU and TE	Felthoven (2002) Alaskan Pollock 1994-2000
How have inputs, outputs or behavior changed when the management or biological environment changed?	
DEA with undesirable outputs	Färe et al. (2011) Georges Bank US/Canada otter trawl 2003-2005
DEA of quantities and regression	Scheld and Walden (2018) NE US groundfish 2007-2014 with IQs and selectivity
How might inputs and outputs change when the management or biological environment changes?	
SFA of profits	Pascoe et al. (2011) Northern prawn 1994-2005 with IQs
SFA and marginal effects of input changes	Pascoe et al. (2017) Moreton Bay prawn trawl 2005-2010 with buybacks

Notes: IND – Index Number Decomposition; TFP – Total Factor Productivity; DEA – Data Envelopment Analysis; SFA – Stochastic Frontier Analysis; CU – Capacity Utilisation; TE – Technical Efficiency

The need for current information on the economic performance of fisheries is well recognised, particularly in Australian fisheries that are managed with an economic objective. Despite this, relatively few fisheries have a time series of economic performance measures. Unlike logbook data that is collected in real time (e.g., e-logs) or shortly after catch has been landed, economic information on costs and earnings, where it is collected at all, is collected after the end of the financial year and business accounts have been finalised. In many cases, such data collection is only undertaken every second year. As a result, the final estimates of profitability are often several years old before they are finalised.

The key productivity measures discussed above are largely based on logbook information and, in some cases, market prices. These are available at a higher frequency than most economic survey data. The estimation of technical efficiency and capacity utilisation are derived from economic theory, and the underlying models have a microeconomic foundation in profit maximisation. As a result, productivity measures should reflect changes and heterogeneity in economic performance in a fishery. Technical efficiency is a component of economic efficiency, and it would be expected that a less efficient fisher would be less profitable than a more efficient fisher, ceteris paribus. Similarly, capacity utilisation should reflect changing economic conditions: higher output prices and lower input prices would be expected to lead to higher capacity utilisation, and higher profitability.

While the theory is sound, to date there has not been any empirical comparison between productivity measures and economic performance measures (such as derived from economic surveys) to test this theory. If such a relationship can be established, then productivity measure can provide more real-time measures of economic performance in fisheries where economic data are also collected, and base level measures of economic performance in fisheries where economic data are not collected. This is in addition to the other potential uses of these productivity measures in terms of informing management decisions (and predicting management outcomes).

We have seen that heterogeneity of fishers has been the underlying driver for most previous studies that estimate capacity, capacity utilisation, and scale, technical and allocative efficiency – if all fishers were the same as a representative fisher, a simple metric would be enough to characterize the fishery. The impact of this heterogeneity is important for the implications of management change, such as determining the likely impacts of buybacks or output quotas on fleet size and harvests. The literature has done this in a relatively ad hoc way, for instance, by identifying the lowest performing subset of fishers in a fishery and noting that these are the ones likely to exit. Explicitly accounting for distributional effects through the use of quantile-style regressions would help address Grifell-Tatjé et al. (2018) call to researchers to consider dispersion, heterogeneity, and inequality more formally.

Understanding fisher behavior and response to incentives is also important. Ex ante predictions regarding the behavioural impacts of management change are likely to need the most detailed combination of bioeconomic modeling and productivity analysis, particularly if the fishery is currently subject to significant input or output constraints. As noted by Cox (2007), productivity analysis should not be conducted for the sake of supporting poor management practices. For instance, capacity analysis used to support a continuing use of buybacks without addressing incentives to encourage effective use, and potentially difficult management change, does a disservice to the value of the resource. Researchers and managers must, therefore, be mindful of the purpose of conducting the analysis.

Implications for case studies

The objective of Part 1 of this project was to provide a literature review about the use of productivity analysis as a performance indicator and in management assessment in fisheries and to assess the contexts in which the literature provides additional insights for effective management.

The review revealed that there has been an evolution in the focus of the literature from early attention to the direct measurement of efficiency and productivity towards asking questions regarding why and how they are at such a level or changes are occurring.

The extant literature only provides a small number of studies that examine productivity analysis of fisheries in the context of Australia. These characterise efficiency and productivity in each of the case study fisheries and have a strong theme of analysing the impact of management change.

Major gaps in the literature include:

- understanding consistency of productivity indicators when we apply different methods of analysis;
- the link between efficiency, capacity utilisation and economic performance;
- the impact of dispersion, heterogeneity, inequality and institutions on outcomes; and
- understanding the behavioural responses of fishers.

Keeping in mind the scope of the project to measure, interpret and monitor economic productivity in commercial fisheries, the method for Part 2 of the project as described above (Case Study Methodology) was developed based on the gaps highlighted in the literature review. That is,

- conduct a multi-model analysis (DEA and SFA) of a selection of Australian fisheries to estimate productivity and efficiency in these fisheries;
- compare these estimates to standard measures of economic performance where available to show when productivity analysis adds value; and
- examine the impact of confounding factors such as heterogeneity, biomass, environment and management constraints where possible.

The following three sections describe the results from taking this approach for each of the three case studies.

Commonwealth Northern Prawn Fishery Case Study

As our benchmark case, we use data from a data-rich fishery, including catch and effort information as well as detailed economic information (i.e., vessel level profitability) to estimate all the productivity measures from different models. The key productivity measures are compared with the economic performance measures, and the strength of the relationship between the different measures is assessed. While economic information could be collected in all fisheries, we will show when and how these productivity measures can provide useful indicators of changes in economic performance when economic information is not available. These indicators can also be used in harvest strategies for data poor fisheries where achieving economic outcomes is a key objective.

Northern Prawn Fishery introduction

The Northern Prawn Fishery is a multispecies fishery located in the tropical region of northern Australia (Figure 11). The fishery is Australia's largest wild-caught prawn fishery, dominated by brown and grooved tiger prawns (*Penaeus esculentus* and *P. semisulcatus*), red and blue endeavour prawns (*Metapenaeus ensis* and *M. endeavouri*) and white banana prawns (*P. merguiensis*), which are mostly caught in the Gulf of Carpentaria. Redleg banana prawns (*P. indicus*) are also caught in a separate geographical region of the fishery (see Figure 11), but are exploited by only a small subset of the fleet (Pascoe et al. 2020, Plagányi et al. 2020).

A number of other species, such as squid (*Loliginidae* spp.), scampi (*Nephropidae sp*.), bugs (*Scyllaridae sp*.), scallops (*Pectinidae sp*.), are caught as incidental bycatch with the targeted prawn catch. In 2019, the gross value product of the fishery was A$117.7 million, A$115.0 million of which was derived from the target prawn species (Patterson et al. 2020).

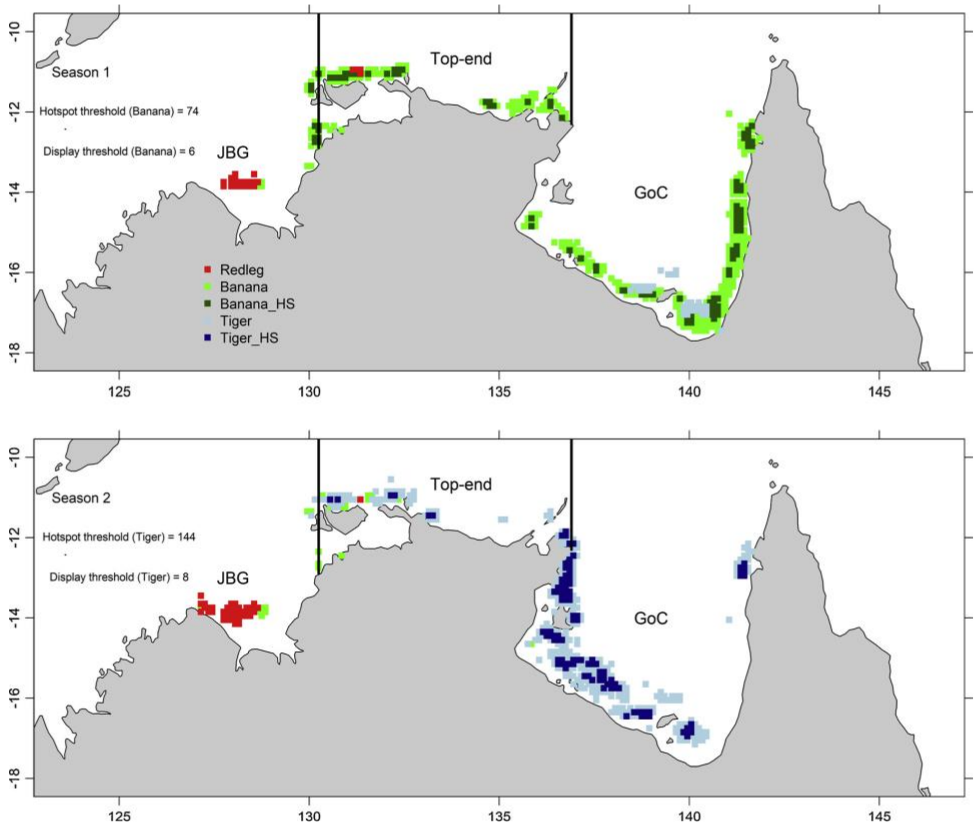


Figure 11. Distribution of effort targeted at banana and tiger prawns across the two fishing seasons in the NPF

Notes: common banana – green; redleg banana – red; tiger – blue). JBG – Joseph Bonaparte Gulf; GoC – Gulf of Carpentaria; HS – hotspot. Source: Pascoe et al. (2020)

As with all Commonwealth managed fisheries, the fishery has an objective of maximising net returns to the community, which is implemented through achieving Maximum Economic Yield (MEY) for the fishery. The fishery is managed using effort controls, including limitations on season length, number of vessels, and total gear length (head rope length). Individual transferable effort (ITE) units, based on fishing gear and days fished, have been in place since 2000, and are used to manage the tiger prawn component of the fishery. A limit on towing more than two nets was lifted from the start of the 2006 fishing season (ABARES 2007). Since then, most vessels have transitioned from using twin gear to using a quad rig comprising four trawl nets (quad gear)—a configuration that is more efficient (ABARES 2020), although each vessel adopting new gear was subject to a 10% penalty on their gear units. The white banana prawn component of the fishery is currently managed using an in-season MEY catch rate trigger (Pascoe et al. 2018).

In addition, several industry and government funded buyback schemes have reduced the fleet from over 300 vessels when the fishery commenced in the early 1970s, to the current 52 vessels. The last major buyback occurred in 2006-07, in which roughly half the fleet was removed.

The fishery has two fishing seasons, separated by a mid-year closure, and effectively forming two sub-fisheries. The first season is dominated by banana prawns, with some tiger and endeavour prawns caught at the end of the first season (depending largely on the size of the banana prawns stock, which varies substantially from year to year largely driven by rainfall (Vance et al. 1985)). The second season is dominated by tiger prawns, with endeavours and a number of other byproduct species caught as bycatch. The lengths of the fishing seasons have changed over time in order to restrict fishing effort, with the shortest fishing seasons (134 days in total) in the years from 2002 to 2004.

The fishery has a long history of efficiency and productivity analysis. Earlier studies tended to focus on one sub-fisheries. For example, Kompas et al. (2004) and Kompas et al. (2009) examined the relationship between input controls and efficiency levels for the banana prawn fishery; Pascoe et al. (2010) examined targeting ability for individual species in the multispecies tiger prawn fishery; Pascoe et al. (2012) examined the impact of the effort reduction (buyback) program on efficiency in the tiger prawn fishery; Pascoe et al. (2018) examined changes in efficiency over the banana prawn fishing season and implications for setting the MEY trigger; and Van Nguyen et al. (2021) examined the sensitivity of model functional form on the efficiency estimates for the banana prawn fishery. Only one study to date has estimated efficiency across the whole fishery: O'Donnell (2012) used aggregate fishery level data to estimate measures of total factor productivity change, environmental change, technical efficiency change, and scale efficiency change over time in the fishery between 1974 and 2010.

Northern Prawn Fishery data

Vessel level catch and effort data were obtained from AFMA logbooks covering the period 1999-2000 to 2019-2020. For consistency with the available economic data, catch and effort for each vessel were aggregated to a financial year level, with separate catch values for common banana prawns, redleg banana prawns, tiger prawns (combining both brown and grooved tiger prawns), endeavour prawns (red and blue endeavour combined) and other prawn species. In total, 1521 observations were obtained, covering 160 different vessels that operated for at least one year in the fishery. Of the 52 vessels currently in the fishery, 35 operated over the full period of the data (Figure 12).

The boat information also included details on the number of days fished, engine power and vessel length. Information on hours fished was also available, but this was considered inaccurate for the earlier years in the time series so was discarded. Price information was also compiled at a financial year (annual) level for each of the species, derived from ABARES reports as well as industry provided price data used in the stock assessment process and estimation of the trigger catch rates. A summary of the key data used in the analysis is given in Table 2.

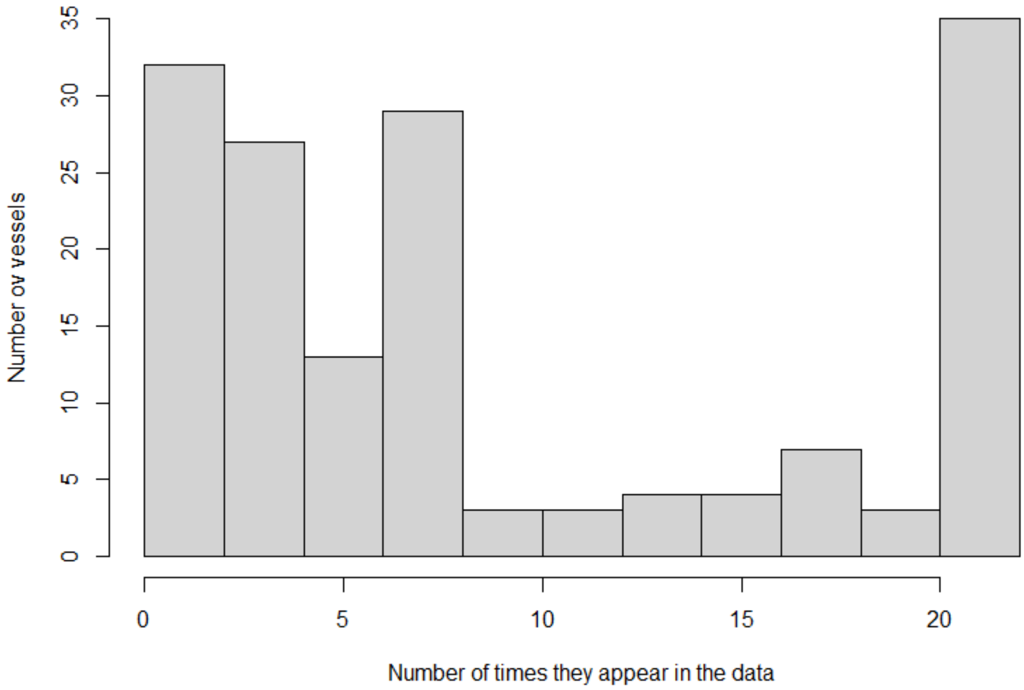


Figure 12. Distribution of vessels in the data, NPF, 1999-2000 to 2019-2020

Economic data over the same period were derived from ABARES economic surveys (e.g., Bath et al. (2019), Bath and Green (2016) and earlier reports). These covered the years 1999-2000 to 2016-17. Data for earlier years were also available, although not used in the study (which was limited to the turn of the century).

Table 2. Summary of catch and effort data used in the NPF analysis

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Catch (kg)						
• Banana prawns	0	23874	45294	54364	78038	231973
• Redleg prawns	0	0	561.5	6885.6	7870.5	90289
• Tiger prawns	0	16940	22219	24134	29043	94028
• Endeavour prawns	0	3953	6068	6990	9322	28000
• Other prawns	0	0	72	294.7	338	18417
Inputs						
• Length (m)	12.8	20.1	22.3	22.29	23.89	32.7
• Engine power (kw)	127	303.5	400	376.9	445	634
• Days fished	6	128	146	140.8	161	193

The economic data were available for a subset of the fleet. In total, 530 observations were available, which were subsequently matched with the efficiency analysis results from the catch and effort data. The key economic parameters of interest were gross margins (i.e., revenue less variable costs, a short-term measure of vessel financial performance), boat cash profits (a short-term measure of vessel financial performance taking into account fixed costs also), boat full equity profits (a longer-term measure of economic performance taking into account capital use costs and adjusting for returns to owners of the capital). These were modified from the original data for consistency with the stock assessment and MEY estimation process, as agreed with Industry:

- For repairs and maintenance, we only included 13.4% of the reported R&M (including gear costs), as a high proportion is fixed (Pascoe et al. 2014). The remainder is included as a fixed cost;
- An imputed cost for owner/operator is included in the measure of boat cash profits (not just full equity profits); and
- A 3.7% economic depreciation rate is applied to boat capital cost in the estimation of full equity profits.

All economic data were inflated to 2019-20 real values using the Consumer Price Index (CPI).

Efficiency and capacity utilisation over time

Data envelopment analysis model results

DEA provides a relative measure of productivity, with the efficiency or capacity utilisation of each vessel based on its performance relative to the set of boats against which it is compared. Common practice is to only compare fishing vessels within the same time period, as apparent differences in productivity between time periods may be due to external factors (i.e., differences in stock conditions) (Tingley et al. 2003).

Technical efficiency, capacity utilisation and scale efficiency were estimated for the fleet for 1999-2000 (start of the time series) and 2019-2020 (most recent year of data) to see if there were any fundamental differences in the distribution of the productivity scores each year.

As noted above, general practice is to consider productivity measures within a given year as differences between years may be influenced by unobserved inputs (e.g., stocks) or changes in economic conditions that affect behaviour. For the purposes of this study, however, capturing the effects of these factors through productivity analyses is a key objective.

Changes in resource abundance will directly affect the revenue and costs of fishing, as will changes in input and output prices. A priori, changes in stock abundance (or other environmental drivers) are likely to affect the observed measure of technical efficiency as they will lead to lower (or higher) levels of output despite no direct changes in either observed inputs or unobserved skill. An improvement in stock abundance, all else being equal, would manifest as an increase in technical efficiency (and vice versa).

Conversely, changes in relative input or output prices will potentially affect capacity utilisation; an increase in input prices relative to output prices would result in fishers fishing less (and vice versa), manifesting itself as reduced capacity utilisation. The capacity utilisation also indicates the presence of excess capacity, which may exist for economic reasons as above, or may be due to overcapitalisation of the fishery – the classic too many boats chasing too many prawns (given the economic conditions in the fishery).

Given this, it would be expected that the productivity measures would not only reflect information on changes in economic performance, but provide a possible explanation for any changes in economic performance.

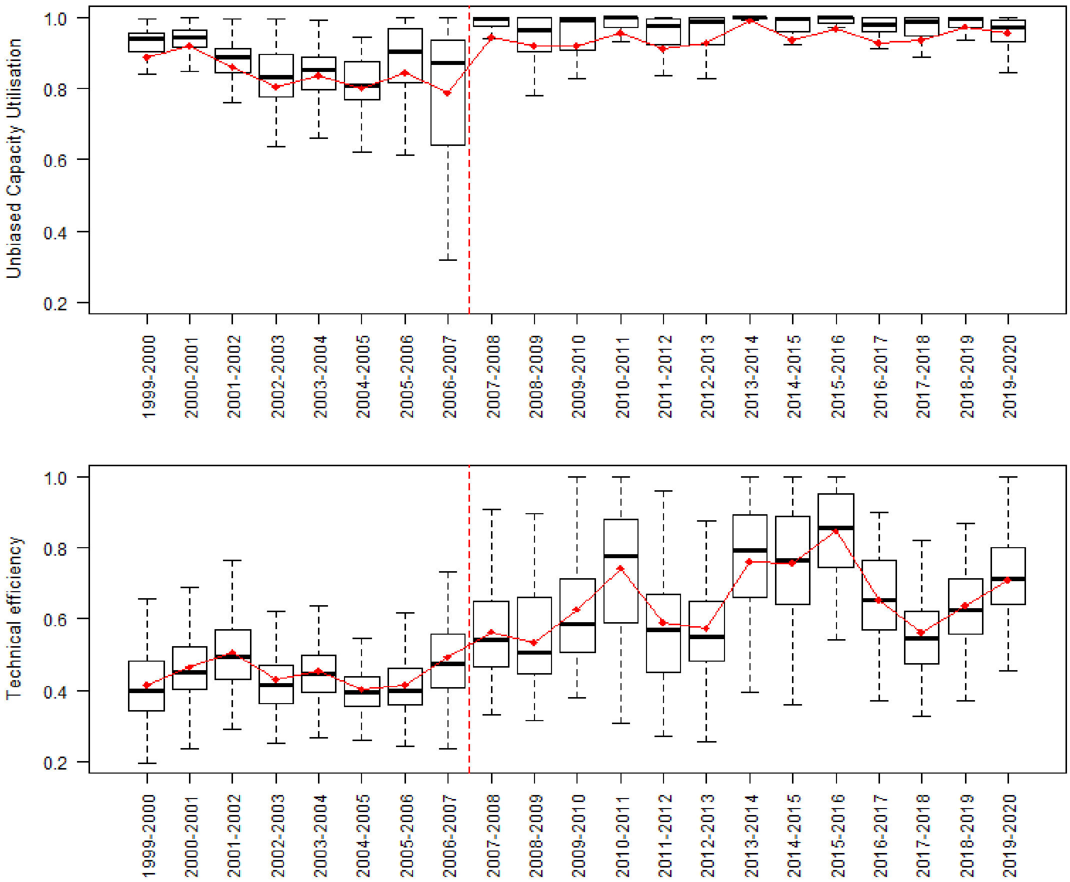


Figure 13. Distributions of key productivity measures, NPF, 1999-2000 to 2019-2020

Notes: The bottom and top of each 'box' indicates the 25th and 75th percentiles (i.e., Q1 and Q3 respectively), the midline indicates the 50th percentile (i.e., Q2 the median), the red dot indicates the mean, and the lines ('whiskers') indicate 1.5(Q3-Q1).*

The distribution of the key productivity scores over the full period of the data (comparing all observations across time) are presented in Figure 13. The dashed red vertical line in Figure 13 represents the last major buyback program, in which the fleet was reduced to 52 boats.

Figure 13 shows the unbiased measure of capacity utilisation was generally lower before the buyback than after, as might be expected as the buyback removed some excess capital from the fishery. From 2007-08, capacity utilisation in the fishery was relatively high, with just small interannual variations.

Technical efficiency levels were also generally lower before the buyback. The gradual increase in technical efficiency after the 2007-08 reflects the recovery of the tiger prawn stocks. This is consistent with other studies that have found that average efficiency increased over time due to the removal of the least efficient vessels through the buyback programs (Pascoe et al. 2012). Reduced crowding post-buyback was also found to have a positive impact on technical efficiency, contributing to the increase in the number of vessels with higher efficiency scores (Pascoe et al. 2012). Scale efficiency (not shown), in most instances, remained above 0.95 for most (at least 75%) of the vessels.

The underlying cause of the apparent greater variability in efficiency scores post-buyback is unknown. Potentially, given a smaller fleet and subsequently more fishing options for the remaining fleet, factors such as skipper skill and 'luck' may play a bigger role than when options were more limited. For instance, the better skippers may be more able to capitalise on the opportunities presented by the smaller fleet size (e.g., less crowding in certain areas) than the less efficient skippers, and hence the increase in efficiency from the buyback was not equally distributed across the fleet.

Stochastic production frontier model results

Unlike the DEA analysis, the stochastic production frontier analysis requires a single measure of output. This requires the catch data to be aggregated. Three approaches were applied. The first involved the use of total (unweighted catch) as the output measure. Second, a Divisia index (Hulten 1973) was estimated, where the catch of each species is weighted by its revenue share. Finally, a measure of total revenue was used. The Divisia index and total revenue measure both require information on prices, which may not always be available.

The different output measures have varying implications for the interpretation of efficiency and capacity utilisation. As both the Divisia index and revenue variables contain information on prices, the measure of technical efficiency also captures elements of allocative efficiency.

As with the DEA approach, the analysis was run with both fixed and variable inputs to estimate technical efficiency, and just fixed inputs to estimate capacity utilisation. The models were run with boat length and engine power as the fixed inputs, and days fished as the variable inputs. The high correlation between boat length and engine power resulted in unreliable model parameters when both used at the same time due to multicollinearity issues. The models were run with each separately, and based on the Akaike Information Criterion (AIC), boat length was chosen as the most appropriate fixed input. While the exclusion of engine power may have an impact on the estimated efficiency scores, an earlier study (Van Nguyen et al. 2021) found that these differences were relatively small.

The treatment of stocks was also a consideration. Initially, the models were run with an annual dummy variable to reflect stock changes at an aggregate level. However, this also captured changes in the efficiency over time of the fishery. The dummy variables were instead included as explanatory variables as part of an inefficiency model (Battese and Coelli 1995). The incorporation of an explicit inefficiency model, however, does not necessary capture vessel-specific characteristics unless these are also included. To ensure that vessel effects are considered, vessel dummy variables were also included in the inefficiency model.

Unlike the DEA approach, separating the efficiency element from the capacity utilisation component to derive an unbiased measure was less straightforward as the estimated model parameters also changed with the change in model structure (i.e., omitting variable inputs in the case of the capacity utilisation models). Similarly, for models using the Divisia index and revenue, the measure of capacity utilisation also contained an element of allocative efficiency.

To provide consistency as far as possible with the DEA approach, the different efficiency measures were derived from combinations of the different models.

- Measure of technical efficiency and capacity utilisation were derived from the model using the total catch measure directly and used in the subsequent analysis;
- Measure of technical efficiency and capacity utilisation were also derived from the model using the Divisia index directly, although these are influenced by allocative efficiency;
- Measure of technical efficiency was derived from the model using the total revenue measure directly and used to derive measures of allocative efficiency by dividing estimated revenue efficiency by technical efficiency from the total catch based model.

The models used to estimate technical efficiency were specified as translog production frontiers, while the model for the capacity utilisation analysis had only one independent variable. All data were logged and normalised, such that $\bar{x} = \bar{y} = 0$.

The model results for the technical efficiency analysis are presented in Table 3, and capacity utilisation models in Table 4. The coefficients for the inefficiency model (20 year dummy variables and 160 vessel dummy variables) are not presented. The likelihood ratio test for the existence of inefficiency was significant in all cases (i.e., testing the model against a standard production function with no inefficiency component).

Table 3. Stochastic frontier model results: TE estimation

	Total catch			Divisia index			Revenue		
	Estimate	Std Err		Estimate	Std Err		Estimate	Std Err	
Intercept	0.066	0.946		0.826	0.034	***	0.397	0.012	***
ln(Length)	1.551	1.000		2.104	0.230	***	1.319	0.136	***
ln(Days)	1.919	0.997	+	0.827	0.059	***	1.033	0.037	***
ln(Length)^2	-2.081	1.000	*	-6.073	1.212	***	-2.470	0.838	**
ln(Days)^2	0.880	1.000		1.171	0.231	***	0.452	0.158	**
ln(Length)*ln(Days)	0.624	1.000		-0.079	0.085		-0.087	0.053	
Mean TE	0.910			0.503			0.711		
Number of obs.	1491			1491			1491		
LR test χ^2	207.3	*		1899.4	***		1834.5	***	
Monotonicity (%)									
Length	99.7			99.1			99.9		
Days	100			100			100		
Quasiconvexity (%)	99.8			100			100		

Significance: *** 0.1%, ** 1%, * 5%, + 10%

The translog production frontiers in Table 3 were tested for theoretical consistency (Sauer et al. 2006). The models were found to be fully monotonic in terms of days fished, and almost fully monotonic in terms of boat length. While methods are available to correct the models to achieve 100% monotonicity in all inputs (Henningsen and Henning 2009), this was not undertaken given the high proportion of monotonic observations. Similarly, quasiconvexity conditions were found to hold for 100% of observations in the models with revenue and Divisia index as the dependent variable, and almost all for the model based on total catch. As the models used to estimate capacity utilisation involved only one variable, tests of theoretical consistency were not necessary.

The model based on total catch had few significant parameters, unlike the models based on revenue and the Divisia index. This suggests that fishers were more likely targeting total value that total catch, consistent with profit maximisation behaviour (Herrero and Pascoe 2003). This relationship was apparent for both the models used to estimate technical efficiency and capacity utilisation (although a revenue-only model was not used for estimating capacity utilisation).

Table 4. Stochastic frontier model results: CU estimation

	Total catch			Divisia index		
	Estimate	Std Error		Estimate	Std Error	
Intercept	0.539	0.501		0.760	0.023	***
ln(Length)	1.917	1.000	+	2.103	2.256	***
Mean CU	0.619			0.531		
Number of obs.	1491			1491		
LR test χ^2	594.6	***		2103.2	***	

Significance: *** 0.1%, ** 1%, * 5%, + 10%

Multi-output distance function model results

The models were also estimated as stochastic multi-output distance functions. As with DEA it estimates a multi-output frontier with the efficiency score based on the distance to the frontier through a radial expansion. The model has the advantage in that it does not require aggregation of the outputs, avoiding some of the limitations of the previous stochastic production frontiers.

The models were estimated with banana prawns as the base (i.e., dependent variable), with the independent variables including the catch of other species normalised by the quantity of banana prawns caught. As some observations had zero catch of some species, zeros were replaced by 0.01 (i.e., 10 grams, less than one small sized prawn). All data were again logged, but unlike in the previous models the data were not normalised such that $\bar{x} = \bar{y} = 0$ (due to a different estimation procedure in the Benchmarking package in R). As with the stochastic production frontiers, and inefficiency model including only year and vessel dummy variables was used to capture the inefficiency component.

The estimated models are presented in Table 5. LR tests for existence of inefficiency were significant for both models. The full inefficiency model components are not presented for concision (i.e., 20 year dummy variables and 160 boat dummy variables). The models were also considered theoretically consistent, although the technical efficiency model did not 100% satisfy convexity assumptions.

Decomposition of technical change and efficiency change over time

The vessel level productivity changes in the form of Malmquist Index (M), technical change index (TC), and efficiency change index (EC) between 1999 and 2019, with 1999 as a base year (M=TC=EC=1) are shown in Figure 14. Values above 1 indicate an increase compared to the previous year, while a value less than 1 indicates a decrease.

The Malmquist Index (M), driven primarily by the technical change index (TC) generally fluctuate over the period of the study, reflecting changes in stock abundance as well as technical improvements and the effects of management. Separating out these effects requires an independent and composite estimate of stock changes between years and could be potentially undertaken as a second-stage analysis. In contrast, the efficiency change index (EC) is relatively stable throughout the study period, centered around 1 (i.e., no change) (Figure 14). This suggests that changes in performance of the fleet are driven by largely exogenous factors impacting catches, with little change in the relative skill of fishers from year to year, particularly when variable returns to scale is assumed (the most common assumption).

Comparison of efficiency scores

A comparison of the technical efficiency scores for all methods applied is given in Figure 15 and correlation between the scores illustrated in Figure 16. As expected, the DEA scores (DEA_TE) were generally lower than those from the stochastic approaches. This is an artifact of the influence of random variation, which is largely removed in the stochastic approaches. The efficiency scores from the model based on total catch (SPF TE Total Catch) appeared to differ the most from those from the other three approaches.

The efficiency scores from the multi-output distance function (Distance TE) were generally correlated with both the DEA results (DEATE, r=0.73) and the results based on the Divisia index (SPFTE Divisia, r=0.79), but correlation between these two other measures was low (r=0.58). The results based on total catch (SPFTE Total Catch) had only a low correlation with the other scores, ranging from 0.47 against DEATE to 0.56 against SPFTE with Divisia.

Unbiased capacity utilisation scores derived from the different approaches are presented in Figure 17. The scores from the DEA (DEAUCU), the model based on catch (SPFUCU Total Catch) and the distance function (DistanceUCU) followed similar trends. In contrast, the scores from the model based on the Divisia index (SPFUCU Divisia) exhibited a substantially different trend. Further, these values were

Table 5. Multi-output distance function models

	Technical efficiency model			Capacity utilisation model		
	Estimate	Std. Error		Estimate	Std. Error	
Intercept	-5.216	0.978	***	-35.962	0.491	***
Length	7.411	0.801	***	28.447	0.467	***
Days	0.648	0.630				
Redleg*	-1.317	0.821		3.482	0.918	***
Tiger*	-1.229	0.914		0.831	0.888	
Endeavour*	0.656	0.971		2.469	0.913	**
Other*	1.046	0.961		-2.960	0.918	**
Length^2	-2.354	0.659	***	-8.351	0.128	***
Length x Days	0.179	0.337				
Length x Redleg*	-0.401	0.438		-1.398	0.274	***
Length x Tiger*	0.185	0.556		-0.319	0.312	
Length x Endeavour*	0.095	0.651		-0.663	0.312	*
Length x Other*	-0.320	0.532		0.844	0.327	**
Days^2	0.025	0.230				
Days x Redleg*	0.143	0.280				
Days x Tiger*	-0.069	0.391				
Days x Endeavour*	-0.293	0.399				
Days x Other*	-0.036	0.334				
Redleg*^2	1.919	0.683	**	0.631	0.482	
Redleg* x Tiger*	-0.204	0.294		-0.290	0.256	
Redleg* x Endeavour*	-0.025	0.540		-0.421	0.483	
Redleg* x Other*	0.004	0.850		0.429	0.646	
Tiger*^2	0.877	0.690		0.395	0.510	
Tiger* x Endeavour*	-0.071	0.342		-0.457	0.217	*
Tiger* x Other*	-0.006	0.575		-0.084	0.384	
Endeavour*^2	0.972	0.805		0.338	0.457	
Endeavour* x Other*	-0.151	0.666		-0.211	0.611	
Other*^2	0.318	0.844		0.181	0.515	
Mean TE	0.735			0.590		
N. obs	1491			1491		
LR	1751.9	***		1926.5	***	
Monotonicity (%)						
Length	100			100		
Days	100			0		
Quasiconvexity (%)	99.9			100		

Significance: *** 0.1%, ** 1%, * 5%, + 10%

Note: Catches in the model are normalised (divided) by banana prawn catch

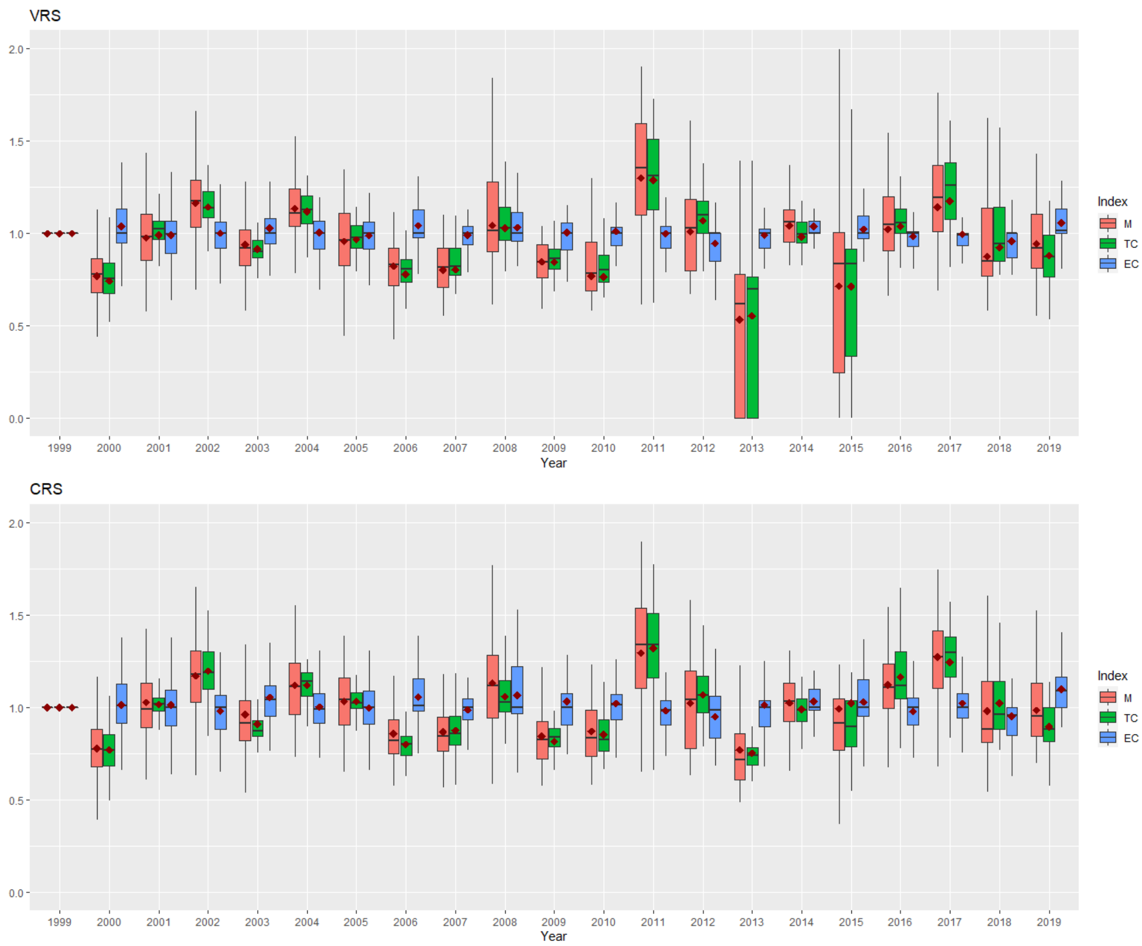


Figure 14. Productivity changes in the Northern Prawn Fishery 1999-2019

Notes: The bottom and top of each 'box' indicates the 25th and 75th percentiles (i.e., Q1 and Q3 respectively), the midline indicates the 50th percentile (i.e., Q2 the median), the red dot indicates the mean, and the lines ('whiskers') indicate 1.5(Q3-Q1). Malmquist function in Benchmarking package in R was used to calculate the indices. Malmquist Index (M), technical change index (TC), and efficiency change index (EC), with variable returns to scale (VRS, top) and constant returns to scale (CRS, bottom).*

largely greater than 1, and in some cases greater than 2. This is a consequence of bias introduced through the omission of relevant variables in the parametric approaches, namely the number of days fished and cross product terms. These factors would have been captured in the error term, which when separated into inefficiency and random error resulted in higher capacity utilisation estimates than derived from the technical efficiency model alone (and consequently estimates of unbiased capacity utilisation greater than 1). Although the potential for this to occur for the model based on total catch and also the distance function existed, it was less predominant. However, a small number of estimated unbiased capacity utilisation scores greater than 1 was found in both of these cases.

The correlation between the unbiased capacity utilisation scores is shown in Figure 18. Correlations between the scores were lower than those observed for the technical efficiency scores.

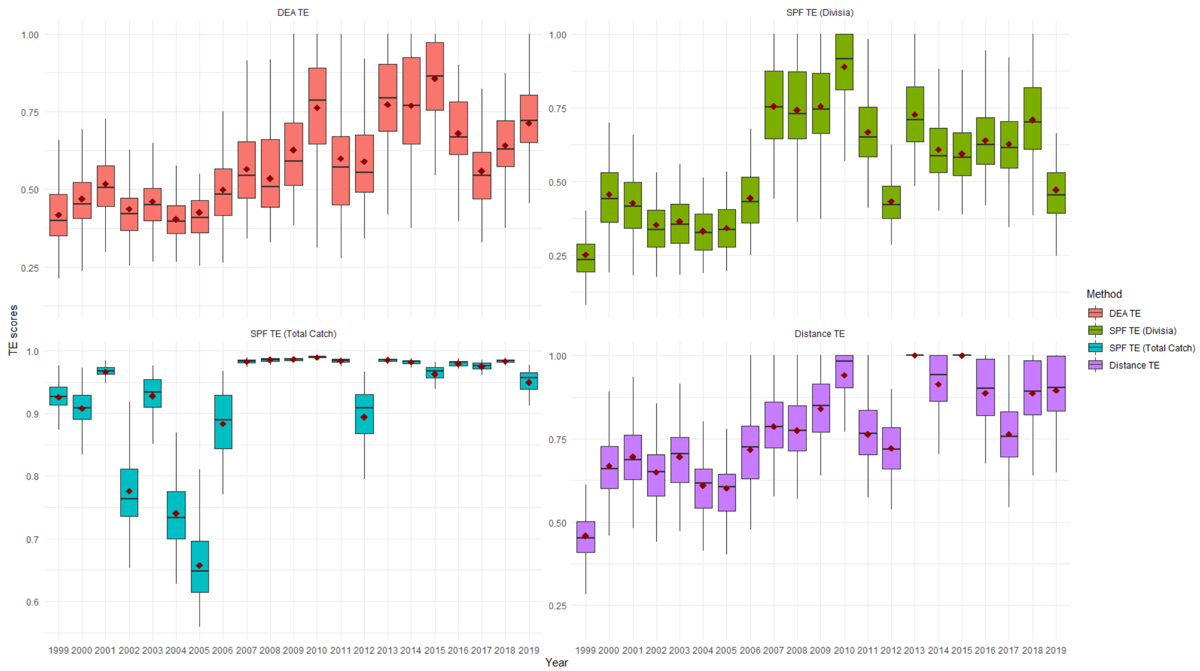


Figure 15. Comparison of technical efficiency scores

Note: The bottom and top of each box indicates the 25th and 75th percentiles (i.e., Q1 and Q3 respectively), the midline indicates the 50th percentile (i.e., Q2 the median), the red dot indicates the mean, and the dashed lines ("whiskers") indicate 1.5(Q3-Q1).*

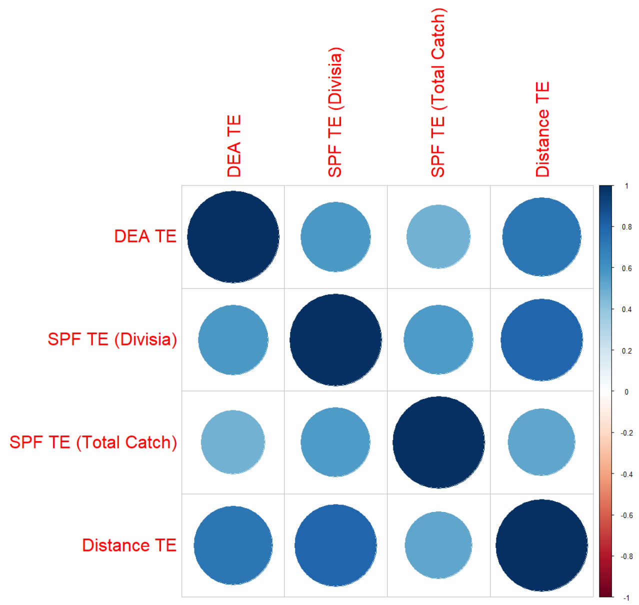


Figure 16. Correlations between technical efficiency scores

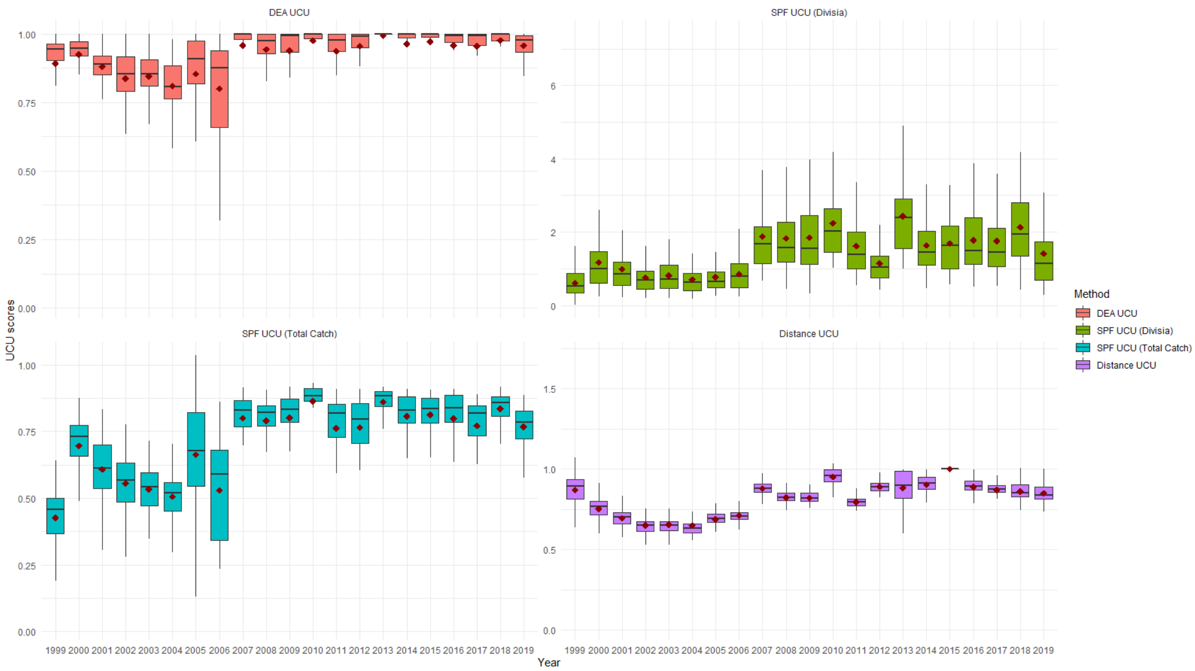


Figure 17. Comparison of unbiased capacity utilisation scores

Note: The bottom and top of each box indicates the 25th and 75th percentiles (i.e., Q1 and Q3 respectively), the midline indicates the 50th percentile (i.e., Q2 the median), the red dot indicates the mean, and the dashed lines ("whiskers") indicate 1.5(Q3-Q1).*

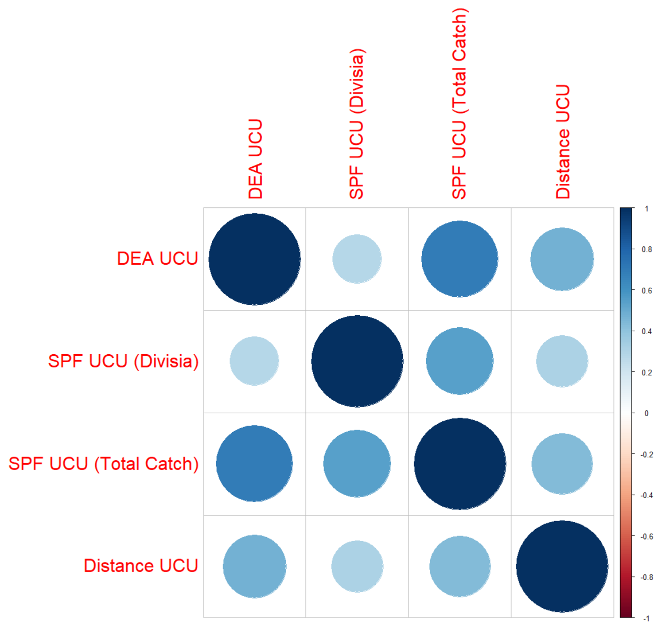


Figure 18. Correlations between unbiased capacity utilisation scores

Relationship between productivity scores and economic performance measures

A key objective of the study is to determine the extent to which the productivity measures can provide information on economic performance in the fishery.

Three key measures of economic performance were extracted from the available vessel level economic data: full equity profits (revenue minus cash and non-cash costs including capital costs), boat cash income (revenue minus all cash costs including fixed and variable costs) and gross margins (revenue minus variable costs). The contribution of technical efficiency and (unbiased) capacity utilisation to these measures was assessed through regression analysis, with the economic measure regressed against the technical efficiency and unbiased capacity utilisation scores. Where available, allocative efficiency was also considered.

As differences in efficiency and capacity utilization are likely to be affected by boat-specific management practices, the models were run as both random effects and fixed effects panel data models. The results of the regression analyses are given in Table 6, Table 7 and Table 8 for the DEA, SPF and distance function analyses respectively.

In all cases, goodness of fit increased as the economic measure accounted for more inputs, that is, from gross margins to full equity profits (Figure 19). Individual boat level economic performance is also affected by factors other than those related to productivity. For example, expenditure on gear or repairs and maintenance may have a substantial impact on economic measures, but largely be unrelated directly to fishing activity. Similarly, other fixed costs, such as, for example, accountancy fees or other administrative fees, may vary between vessels for reasons not related to their fishing activity. Removing fixed costs (as in the case of gross margins) provides an economic measure most closely related to catch and effort, and best captured by productivity measures.

The productivity measures from most models performed similar in terms of explanatory power of economic performance, with the exception of the model based on the Divisia index. As noted previously, this model also was problematic in terms of estimation of unbiased capacity utilisation.

Hausman (1978) tests comparing the fixed and random effects specification gave varying results. In the stochastic modelling approaches, the test statistic was generally significant, suggesting that the models were significantly different and that there is potential correlation between the independent variables in the random effects models and the error term. However, Clark and Linzer (2015) suggests that this does not necessarily mean that the fixed effects model is better. The value of theta ($0 < \theta < 1$) also provides a guide as to the relative importance of idiosyncratic and individual effects, with a value of $\theta = 0$ suggesting that all variation is random (i.e., no fixed effects) and a value of $\theta = 1$ suggesting all variation is fixed. In all cases, the mean value of θ was less than 0.6, and often less than 0.3, suggesting that a fixed effects specification may have been inappropriate.

In most cases, both technical efficiency and unbiased capacity utilisation were found to be significant factors affecting economic performance. Allocative efficiency was found to be not significant in the case of the DEA based analysis, but significant in the case derived from the SFA models based on total catch and total revenue. However, in this case, the measure of capacity utilisation became non-significant. Correlation between these two measures was low (r=0.36) so it is unlikely that multicollinearity was a cause of this.

As the data in the regression models are logged, the parameter estimates represent the estimated economic performance elasticities (i.e., the responsiveness of the economic performance measure to a 1% change in technical efficiency and capacity utilisation). From the above tables, the two multi-output approaches (DEA and the distance function) were broadly similar in magnitude (Figure 20). In contrast, the results for the stochastic production frontiers were substantially different, potentially reflecting the issues around capacity utilisation estimation.

Table 6. Data Envelopment Analysis based results

	Full equity profits						Boat Cash Profits						Gross Margins					
	Random effects			Fixed effects			Random effects			Fixed effects			Random effects			Fixed effects		
	Estimate	Std. Er		Estimate	Std. Er		Estimate	Std. Er		Estimate	Std. E		Estimate	Std. E		Estimate	Std. E	
Excluding allocative efficiency																		
Intercept	13.412	0.103	***				13.366	0.113	***				13.971	0.072	***			
ln (TE)	0.843	0.150	***	1.018	0.183	***	0.879	0.171	***	0.945	0.210	***	0.546	0.082	***	0.507	0.085	***
ln (UCU)	1.026	0.280	***	1.033	0.311	***	1.075	0.503	*	1.229	0.585	*	0.651	0.139	***	0.708	0.139	***
$\bar{\theta}$	0.265						0.310						0.583					
R^2	0.623			0.111			0.675			0.093			0.903			0.128		
$\bar{R}^2$	0.621			-0.057			0.674			-0.097			0.902			-0.011		
Hausman χ^2				2.935						1.120						32.423	***	
Including allocative efficiency																		
Intercept	13.425	0.121	***				13.404	0.136	***				14.053	0.082	***			
ln (TE)	0.841	0.150	***	1.020	0.184	***	0.880	0.171	***	0.950	0.213	***	0.539	0.082	***	0.504	0.085	***
ln (UCU)	1.011	0.291	***	1.007	0.328	**	0.991	0.531	.	1.187	0.650	.	0.577	0.144	***	0.663	0.145	***
ln (AE)	0.043	0.223		0.069	0.275		0.128	0.256		0.047	0.318		0.242	0.124	.	0.150	0.131	
$\bar{\theta}$	0.266						0.309						0.573					
R^2	0.625			0.111			0.675			0.093			0.903			0.130		
$\bar{R}^2$	0.623			-0.059			0.673			-0.100			0.903			-0.011		
Hausman χ^2				3.199						1.444						36.001	***	

Significance: 0***, 0.001**, 0.01*, 0.05., 0.1’

Table 7. Stochastic Production Frontier based results

	Full equity profits						Boat Cash Profits						Gross Margins					
	Random effects			Fixed effects			Random effects			Fixed effects			Random effects			Fixed effects		
	Estimate	Std Err		Estimate	Std Err		Estimate	Std Err		Estimate	Std Err		Estimate	Std Err		Estimate	Std Err	
Divisia index																		
Intercept	13.091	0.138	***				13.100	0.155	***				13.744	0.098	***			
ln (TE)	0.363	0.159	*	-0.195	0.241		0.427	0.177	*	-0.174	0.262		0.235	0.102	*	0.024	0.119	
ln (UCU)	-0.027	0.106		0.489	0.173	**	-0.090	0.118		0.433	0.188	*	0.009	0.072		0.184	0.087	*
$\bar{\theta}$	0.211						0.251						0.561					
R^2	0.496			0.028			0.578			0.022			0.893			0.025		
$\bar{R}^2$	0.494			-0.155			0.576			-0.184			0.892			-0.131		
Hausman χ^2				14.331	***					12.843	*					13.296	**	
Total catch																		
Intercept	13.297	0.083	***				13.281	0.098	***				13.956	0.058	***			
ln (TE)	2.208	0.500	***	2.225	0.541	***	2.205	0.647	***	2.267	0.686	**	1.839	0.234	***	1.623	0.233	***
ln (UCU)	0.816	0.158	***	1.127	0.191	***	0.990	0.213	***	1.199	0.253	***	0.567	0.079	***	0.597	0.082	***
$\bar{\theta}$	0.258						0.308						0.551					
R^2	0.617			0.120			0.677			0.103			0.910			0.176		
$\bar{R}^2$	0.615			-0.046			0.675			-0.085			0.909			0.044		
Hausman χ^2				8.834	*					2.331						58.018	***	
Total catch including allocative efficiency																		
Intercept	13.508	0.085	***				13.446	0.100	***				14.153	0.056	***			
ln (TE)	2.530	0.467	***	2.863	0.498	***	2.865	0.614	***	3.123	0.640	***	2.008	0.208	***	1.876	0.209	***
ln (UCU)	0.179	0.165		0.386	0.191	*	0.337	0.221		0.328	0.255		0.183	0.077	*	0.241	0.079	**
ln (AE)	1.935	0.211	***	2.218	0.233	***	1.826	0.240	***	2.172	0.259	***	1.390	0.109	***	1.323	0.112	***
$\bar{\theta}$	0.331						0.373						0.580					
R^2	0.733			0.268			0.753			0.242			0.927			0.343		
$\bar{R}^2$	0.731			0.128			0.751			0.080			0.927			0.237		
Hausman χ^2				18.071	***					15.689	**					0.636		

Significance: 0***, 0.001**, 0.01*, 0.05., 0.1’

Table 8. Distance function based results

	Full equity profits						Boat Cash Profits						Gross Margins					
	Random effects			Fixed effects			Random effects			Fixed effects			Random effects			Fixed effects		
	Estimate	Std Err		Estimate	Std Err		Estimate	Std Err		Estimate	Std Err		Estimate	Std Err		Estimate	Std Err	
Excluding allocative efficiency																		
Intercept	13.303	0.100	***				13.261	0.111	***				13.897	0.075	***			
ln (TE)	0.471	0.211	*	0.885	0.285	**	0.564	0.232	*	0.725	0.308	*	0.395	0.125	**	0.402	0.135	**
ln (UCU)	1.341	0.287	***	1.708	0.343	***	1.269	0.316	***	1.807	0.373	***	0.781	0.162	***	0.955	0.168	***
$\bar{\theta}$	0.278						0.321						0.593					
R^2	0.623			0.087			0.675			0.084			0.896			0.084		
$\bar{R}^2$	0.622			-0.084			0.674			-0.108			0.895			-0.063		
Hausman χ^2				8.658	*					8.108	*					14.144	***	

Significance: 0***, 0.001**, 0.01*, 0.05., 0.1’

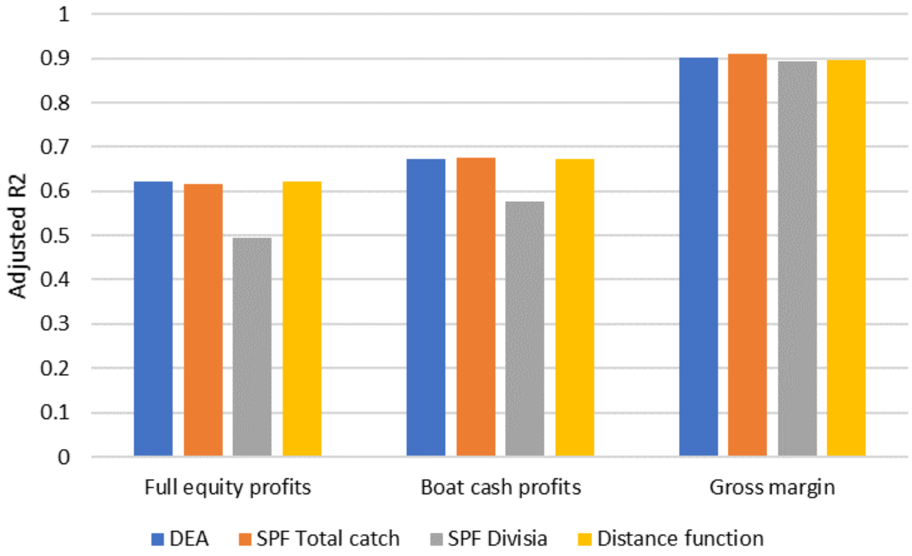


Figure 19. Comparison of adjusted R^2 of each approach in terms of explaining economic performance, random effects models

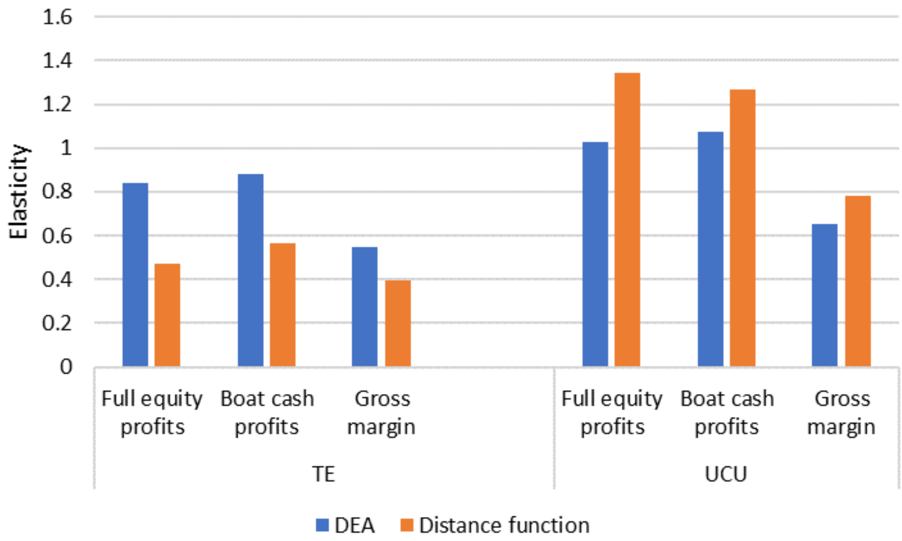


Figure 20. Derived economic performance elasticities

Northern Prawn Fishery discussion

The Northern Prawn Fishery has a rich history of individual data allowing a multi-modal approach to identify consistency of measures and consideration of the relationship between quantity measures of productivity and economic outcomes. All modelling approaches show that technical efficiency and capacity utilization have risen since the major restructuring (buyback) program in 2006-07, consistent with previous studies of the fishery (e.g. Pascoe et al. 2012), although variability in individual outcomes remains.

The results of the comparative analysis suggest that there is a relationship between productivity measures and measures of economic performance, as expected. Improvements in technical efficiency, as measured in the study, reflects both technological improvement as well as resource improvements, resulting in higher catch per unit of effort and higher levels of profitability. The measure of unbiased capacity utilisation is a measure net of these improvements, and reflects changes in the economic environment (i.e., changes in prices or costs). An improvement in unbiased capacity utilisation reflects the behavioural response to these changes, consistent with profit maximising behaviour.

The analysis also showed that the measures of technical efficiency and unbiased capacity utilisation are sensitive to the methods used in their estimation. The use of parametric approaches (i.e., SPF-based models) results in particular problems for the estimation of unbiased capacity utilisation, as exclusion of variable inputs in the model results in omitted variable bias and inconsistencies between the model used to estimate technical efficiency and that used to estimate capacity utilisation. Previous applications of stochastic production frontiers in a capacity context (e.g. Kirkley et al. 2004) estimated only capacity utilisation rather than unbiased capacity utilisation. In the case of the model based on the Divisia index, this resulted in unrealistic estimates of unbiased capacity utilisation. The use of single-output-based models in multi-output fisheries adds an additional complexity as the productivity estimates are sensitive to the way in which the data are aggregated.

Addition of price information allows the estimation of allocative efficiency in some modelling approaches. However, where this was estimated, inclusion of this into the analysis did not seem to be significant in terms of improving the economic model performance.

Based on the comparison of model results in this case study, DEA is the most appropriate approach for estimating indicators of changes in economic performance. A commonly raised 'weakness' of DEA, namely that it does not account for random error, is a potential strength when considering economic performance, as 'random' increases or decreases in catch will also be associated with equivalent changes in revenue. Removing these random changes to provide a more robust efficiency estimate results in these measures being less related to revenue and other economic performance measures. As identified in the broader fisheries productivity literature, DEA is also more appropriate for estimates of unbiased capacity utilisation, particularly in multispecies fisheries such as the NPF. Including only fixed inputs into regression models results in a non-trivial change in the model structure. This results in inconsistencies in the measure of technical efficiency and capacity utilisation, in some cases resulting in unbiased estimates of capacity utilisation greater than 1.

This is not to say that stochastic approaches are not beneficial for other purposes; previous studies in the fishery have demonstrated the usefulness of such approaches for estimating the impact of management changes on efficiency (Kompas et al. 2004, Pascoe et al. 2010, Pascoe et al. 2012), and implications of efficiency changes for management (Pascoe et al. 2018). The use of stochastic distance functions also provides additional information, such as the potential for output substitution and targeting ability (e.g. Pascoe et al. 2010). Multi-output distance functions also remove the issue of aggregation. From the analysis in this study, how catch is aggregated into a single output affected the efficiency scores and the other derived productivity measures.

South Australian Spencer Gulf and West Coast Prawn Fisheries Case Study

Fishers and fishing vessels are not homogeneous, with their level of catch affected by the choice of physical inputs such as engine size, boat size and the type of fishing technology employed, as well as less tangible factors such as skipper skill and experience. Economic output also depends upon the physical biomass and the value of the product in the market. Differences in the ability of individual fishers to catch fish under different biomass and market conditions can be assessed through the application of economic efficiency and productivity analysis.

The SA Spencer Gulf and West Coast Prawn Fisheries provide an informative scenario with which to highlight how different measures of output and performance contribute to a deeper understanding of a fishery. In particular, we use quantity measures to estimate technical efficiency and capacity utilisation, then include value information to estimate allocative, cost, and profit efficiency. These measures are contrasted with one-another and with a longer series of revenue, cost and profit data.

Spencer Gulf and West Coast Prawn Fisheries introduction

The SA Spencer Gulf (SGPF) and West Coast (WCPF) Prawn Fisheries are two of the three commercial prawn fisheries in South Australia, the Gulf of St Vincent Prawn Fishery (GSVPF) is the third (Figure 21). The SGPF is the largest of the three with 39 licences, with a further three and ten licences in the WCPF and GSVPF respectively (PIRSA 2010, PIRSA 2020).

This study examines the Spencer Gulf and West Coast Prawn Fisheries (SGWCPF) together as they are managed in parallel, are both represented by the Spencer Gulf and West Coast Prawn Fishermen's Association, and economic data are reported together to maintain confidentiality of the small WCPF.

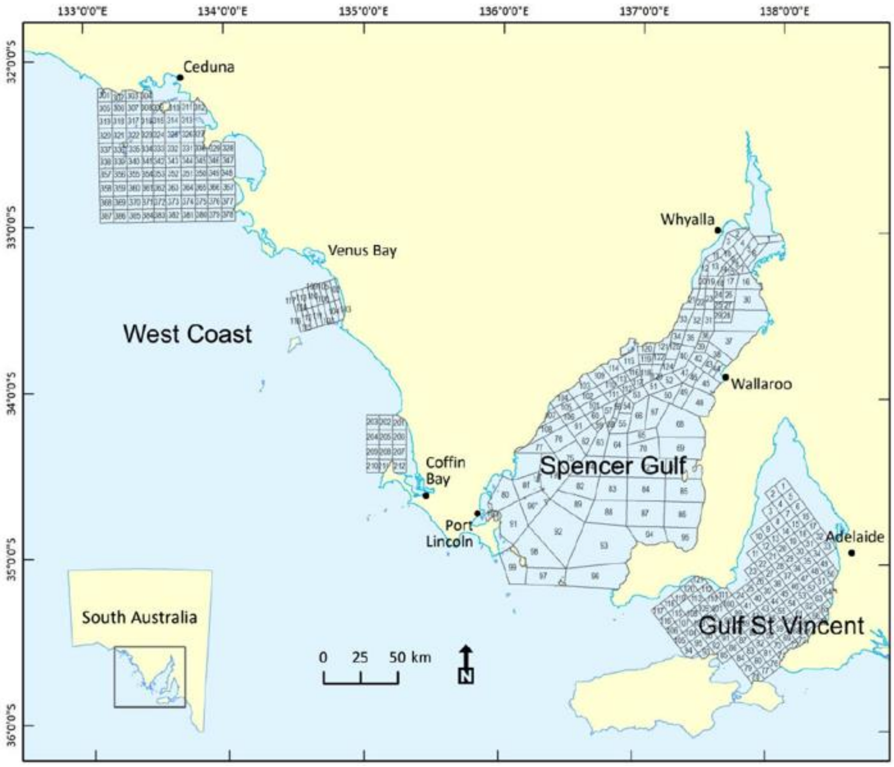


Figure 21. Map of SA commercial prawn fisheries

Source: PIRSA (2020)

They are single-species prawn fisheries, capturing Western King Prawn; in addition blue swimmer crabs and calamari that is harvested incidentally may be retained and sold. In 2011, the SGPF was the first prawn fishery in Australia to be Marine Stewardship Council certified and was recertified for five years from 2016.

Average annual catch over the last 20 years in the SGWCPF fisheries is approximately 2,000 tonnes, worth in excess of $40 million, with 90-100% from the Spencer Gulf. Catch has been variable with annual percentage changes of more than 30% lower (once) or higher (four times) (BDO EconSearch 2018, BDO EconSearch 2020).

The SGPF management plan (PIRSA 2020) establishes four goals for the fishery:

1. Maintain ecologically sustainable prawn biomass. Achieved via management controls on fishing effort including: a restricted number of licences; mesh and head line length restrictions; gear, area and time limits; closed areas (waters <10m); engine power and vessel size. Information from logbooks, surveys and stock status conducted and reported.
2. Ensure optimal utilisation and equitable distribution. Achieved via flexibility within the Harvest Strategy and measures of economic performance are collected.
3. Minimise impacts on the ecosystems. Achieved via fishing effort restrictions (as above); ESD risk assessment; codes of practice; technology to reduce impacts investigated.
4. Enable effective and participative management of the fishery. Achieved via delegation and a degree of co-management with SGWCPFA.

This means the fisheries are input-controlled fisheries with requirements to collect biological and economic information and collaboration with industry is conducted with the SGWCPFA.

The SGWCPFA plays an important role in practical fisheries management of the Harvest Strategy via the Committee-at-Sea. The Committee-at-Sea consists of a Coordinator-at-Sea and skippers, who monitor fished areas in real-time and implement alternative fishing strategies depending upon movement and size of prawns and fishing effort and catch rates. This formal process began in 1992 following informal 'gentlemen's agreements' of the 1970s and '80s (PIRSA 2020). This 'real-time management' has been adapted and refined in the second and third management plans, of 2007 and 2014 respectively, but the underlying principles of industry-coordinated, input-controlled management have been retained.

Spencer Gulf and West Coast Prawn economic data

As part of the fulfillment of the management goal, confidential vessel-level economic data is collected from surveys undertaken by BDO EconSearch in 1997/98, 2000/01, 2004/05, 2007/08, 2012/13, 2015/16, and 2018/19. The surveys were completed by a quarter to a half of license holders in each period. As described in the BDO EconSearch reports, (e.g., BDO EconSearch (2020)), we have boat-level data on revenues, fixed and variable costs, labour and capital characteristics, and catch (since 2007/08). A complete description of the data items is shown in Table 9 and means of key variables are shown in Table 10.

The primary purpose of the surveys is economic performance, hence the focus on value data. The surveys provide detailed information on the quantity of labour inputs (paid and unpaid, and offshore and onshore) and the various costs of fishing, importantly decomposing costs into: variable costs that depend on how much fishing is undertaken (that is, fuel, repairs and maintenance, provisions, and paid and unpaid labour); fixed costs that are independent of the amount of fishing undertaken in a season (that is, licence fee, office costs, etc.); and value and depreciation costs of boat, engine and equipment. The value of outputs, split between Western King Prawn (WKP) revenue and Other (i.e. incidental catch of other species) revenue is reported. Since 2008 the number of nights fished and total catch, and since 2012 boat length and catch split between WKP and Other, have also been included in the survey. These quantity metrics are required for the productivity and efficiency analysis, hence our analysis presents results for these metrics since 2012.

Table 9. Spencer Gulf and West Coast Prawn survey items

	Total Boat Gross Income	**Labour**	**Other Fishing Gear**
	freight/ unloading fees*	Paid & unpaid:	Current Value
(1)	**Gross income (freight, commission deducted)**	Full-time (persons)	Replacement cost
		Part-time (persons)	Estimated depreciation
	Variable costs:	FTE	
	Fuel	Unpaid:	**Land Based Capital**
	Repairs & Maintenance	Fishing (days)	Current Value
	Provisions	Repairs & Maintenance (days)	Replacement cost
	Labour - paid	Management & Admin (days)	Estimated depreciation
(2)	Labour - unpaid	Total Unpaid (days)	
	Other	Ratio Variable to Fixed Unpaid Labour:	**Boat Length (m)***
(3)	**Total Variable Costs**	Variable	
	Fixed costs:	Fixed	**Nights Fished****
	Licence Fee		
	Insurance	**Fishing Gear & Equipment**	**Income**
(4)	Interest	**Boat engine**	Western King Prawn Sales
(5)	Labour - unpaid	Age	Other Sales
(6)	Leasing	Current Value	**Total*****
	Legal & Accounting	Replacement cost	**Catch (tonnes)**
	Telephone etc.	Estimated depreciation	Western King Prawn*
	Slipping & Mooring		Other*
	Travel	**Boat (without engine)**	**Total****
	Office & Admin	Age	
(7)	**Total Fixed Costs**	Current Value	
(8)	**Total Boat Cash Costs (3 + 7)**	Replacement cost	
	Boat Gross Margin (1 - 3)	Estimated depreciation	
(9)	Total Unpaid Labour		
	Gross Operating Surplus (1 - 8 + 9)	**Electronic Equipment**	
(10)	**Boat Cash Income (1 - 8)**	Age	
(11)	**Depreciation**	Current Value	
(12)	**Boat Business Profit (10 - 11)**	Replacement cost	
(13)	**Profit at full Equity (12 + 4 + 6)**	Estimated depreciation	
	Boat Capital:		
(14)	Fishing Gear & Equipment		
	Licence Value		
(15)	**Total Boat Capital**		
	Rate of Return on Fishing Gear & Equip (13 / 14 * 100)		
	Rate of Return on Total Boat Capital (13 / 15 * 100)		

*Notes: *only available since 2012. ** only available since 2008. *** only WKP income available 2008.*

Table 10. Spencer Gulf and West Coast Prawn survey means

	1997-98	2000-01	2004-05	2007-08	2012-13	2015-16	2018-19
Full Equity Profit ($)	128,764	228,756	72,715	85,669	95,214	177,180	185,598
Gross Income ($)	410,868	646,340	513,288	589,691	628,322	883,238	979,478
Total Catch (tonnes)				48.55	47.19	54.67	54.59
Observations/Fishery	9/42	11/42	22/42	17/42	22/39	18/39	11/39

Source: BDO EconSearch provided access to this data as part of this FRDC Project. Values converted to real 2019 using the Australian consumer price index.

Spencer Gulf and West Coast Prawn DEA results

In our first step we use DEA analysis as described above (Case Study Methodology). In theory, the method allows for *N* inputs and *M* outputs. In practice, the number of inputs and outputs to use, and their associated values, is restricted by the data available. In this case study, the cost (input value) data is detailed but the input quantities recorded are limited. We allocate subsets of costs to the most relevant input quantity from those available. As such, the production technology allows for two outputs and three inputs. The two outputs, Western King Prawn, and Other are measured by catch (tonnes) and sales (dollars). The three inputs are: Boat Variable Costs (fuel, repairs and maintenance, provisions, other) with quantity measured by Nights Fished; Labour Variable Costs (paid and unpaid labour) with quantity measured by Labour Full-time Equivalent; and Fixed Costs with quantity measured by Boat Length.

We note that measuring labour inputs in fisheries needs some caution as crew are not typically employed or paid on an hourly basis. The measure reported is full-time equivalent workers, and includes work onshore. The typical payment is that approximately one-third of revenue is paid to skipper and crew. The measure of labour varies from one to 6.5 FTE so there are differences in production. We examine quantities and values separately and together below. Additionally, aligning fixed costs with boat length may not be a direct relationship but boat length is quite homogeneous in this fishery with two-thirds of observations being the same length (22m) and all others within 10% of this. This means that the variation in fixed costs in the value-based analysis is largely occurring irrespective of boat length.

Technical efficiency and capacity utilisation

Using just quantities, that is, without values, we can calculate technical efficiency (TE) and unbiased capacity utilisation (UCU). The closer these measures are to one, the more technically efficient the boat is and the more utilised is capacity. Figure 22 and Table 11 presents TE and UCU for the three survey years that included quantity measures.

We see that the TE scores are relatively high: the means are above 0.8 in all periods with a minimum of 0.66 in 2015-16, which contrasts with the lower means and larger variance estimated for the Northern Prawn fishery. This indicates a relatively homogenous fleet in terms of the quantities of inputs (boat length, nights fished, labour) used to produce outputs (catch of WKP and other). The TE scores are lowest on average in the earliest period, most vessels improved their TE score in 2015-16 (excepting three outliers), and mean TE remained above 0.9 in 2018-19.

UCU is also lowest and with greatest variation in the earliest period, although only slightly below 1. However, it must be noted that the input restrictions used in this fishery put an upper bound on the

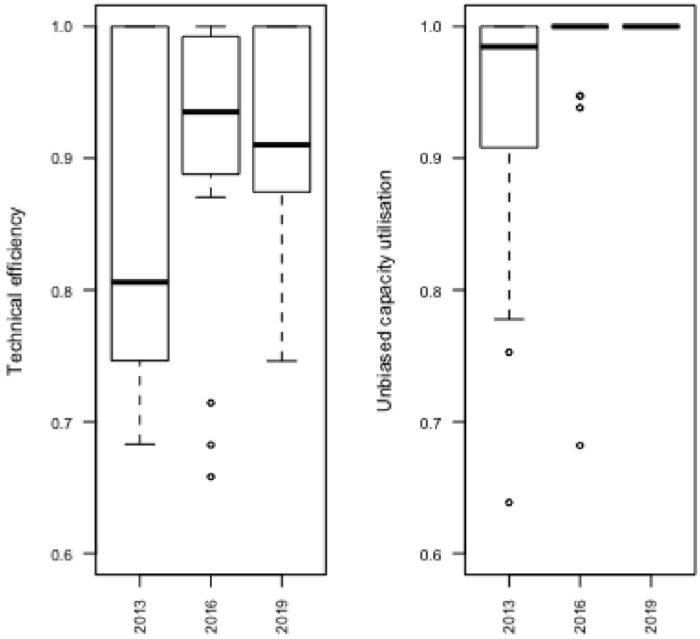


Figure 22. Spencer Gulf and West Coast Prawn TE and UCU

*Note: For each year, the bottom of the box (bar) indicates the 25th percentile, the dark midline indicates 50th percentile (median), the top of the box indicates the 75th percentile, and the whiskers indicate 1.5*Interquartile range up to maximum/minimum.*

inputs that can be used. Hence it is difficult to get an estimate of the 'true' capacity for what could be caught with the current fixed inputs but using an unrestricted number of days at sea. This is because the frontier – the most efficient vessels – are identified from within the observed sample and face the same restrictions. Together, the TE and UCU estimates suggest that vessels are using their variable inputs efficiently, and commensurately with the capital that is available, given the constraints.

Table 11. Spencer Gulf and West Coast Prawn efficiency estimates (Mean, SD)

	2012-13	2015-16	2018-19	Total
Technical Efficiency	0.848	0.905	0.913	0.882
	(0.120)	(0.110)	(0.094)	(0.114)
Unbiased Capacity	0.933	0.973	1	0.962
Utilisation	(0.099)	(0.076)	(0)	(0.083)
Allocative Efficiency	0.978	0.951	0.943	0.961
	(0.022)	(0.037)	(0.048)	(0.037)
Cost Efficiency	0.950	0.932	0.918	0.937
	(0.035)	(0.046)	(0.070)	(0.049)
Profit Efficiency	0.922	0.888	0.893	0.904
	(0.029)	(0.032)	(0.066)	(0.044)

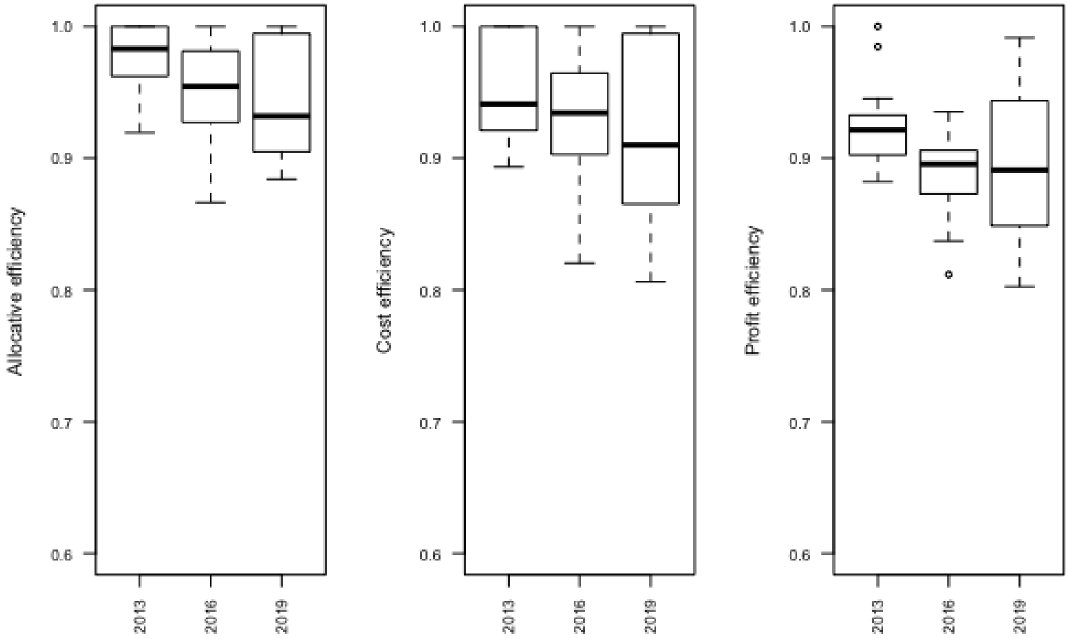


Figure 23. Spencer Gulf and West Coast Prawn AE, CE and PE

*Note: For each year, the bottom of the box (bar) indicates the 25th percentile, the dark midline indicates 50th percentile (median), the top of the box indicates the 75th percentile, and the whiskers indicate 1.5*Interquartile range up to maximum/minimum.*

Allocative, cost and profit efficiency

We now take advantage of the economic information-rich nature of the South Australian data and estimate allocative (AE), cost (CE), and profit efficiency (PE). Again, the closer these measures are to one, the more efficient the firm is at determining the optimal input-output mix given the input costs and output prices faced. Figure 23 and Table 11 presents AE, CE and PE scores for the three survey years for which both quantity and value information is available. The scores are, again, relatively high, indicating a relatively homogeneous fleet. However, when we include the value information, an alternative picture begins to emerge in this fishery as the means of all three measures are falling across time, and the interquartile range is expanding. This indicates that firms are experiencing increasing heterogeneity in their input costs and output prices and how they manage those differences in their input and output mix is impacting upon their profit efficiency.

Second-stage analysis

As identified in Figure 3, further analysis to determine the drivers of efficiency is possible when appropriate biomass or environmental data is available. If management has undergone significant change, this can also be evaluated. The second-stage analysis could be conducted by taking the estimated technical efficiency (or other) scores as the dependent variable and regressing them on relevant biomass, environmental or management variables or, if there is a simple binary measure of before-and-after (e.g., for management change) then a straightforward t-test of differences in means might be more appropriate. Alternatively, estimating efficiency with stochastic frontier analysis, rather than DEA, allows the second-stage to be jointly estimated with the production function (see Productivity Measures and Methodologies). We face several challenges that preclude a second-stage for this case study.

Firstly, the primary challenge is that our analysis covers just three years of data. This means that, while we have multiple firm-level observations in each period, there will only be, at most, three different values for biomass, environment or management. Statistical analysis is, therefore, unlikely to yield relevant and robust results.

Secondly, the stock estimates available for this fishery rely on a catch per unit effort measure. While the estimate is not based on the same vessel-level data, the average measure of technical efficiency in this fishery is likely to move in a correlated way with the CPUE estimate of biomass (especially given the first challenge above). As such, any truly independent changes in biomass are unlikely to be captured, and hence the statistical analysis potentially misleading.

Thirdly, management has remained relatively constant over the period for this fishery. This means that conducting a program-evaluation type analysis is not a relevant question to address here. Although, even if it were, three years of data would only allow one-period before or after so strong conclusions would be unlikely.

Relationship between efficiency metrics and profit

A key objective of the study is to determine the extent to which the productivity measures can provide information on economic performance in the fishery. To do this, we calculate the correlation between the DEA measures of efficiency and measures of economic performance such as income or profits.

We use three measures of economic performance from Table 9 that move from short-term to long-term metrics. Gross Margin is a short-term indicator of performance as it only subtracts variable costs from income; Boat Business Profit accounts for variable, fixed and depreciation costs; and Profit at Full Equity adjusts for interest and leasing payments.

Table 12 shows the results for the same log-linear specification used for the NPF in the previous section that only includes observations with positive economic metrics. We can see there is a positive correlation between UCU with each of our economic performance measures (the coefficients are positive and statistically different from zero), and a positive relationship between TE and Gross Margins. However, the overall relationship is not particularly strong (R^2 is low). We note that, unlike for the NPF, it is not possible to identify vessels across time. As such, panel data methods accounting for individual vessel effects could not be used to estimate the models.

While we note above that examining the impact of stock changes on efficiency is unlikely to give statistically meaningful results, we include it as an additional explanatory variable in the regressions of economic performance. As can be seen in the right-hand of each column below (italicised), stock

Table 12. Spencer Gulf and West Coast Prawn economic performance v TE and UCU

	Full equity profits		Boat business profits		Gross margins	
		with stock		*with stock*		*with stock*
log (TE)	1.343~	*1.341~*	1.425	*1.443*	1.232**	*1.248***
	(0.771)	*(0.780)*	(0.958)	*(0.955)*	(0.428)	*(0.430)*
log (UCU)	4.009***	*4.006****	2.815~	*2.714.*	1.803***	*1.797****
	(1.021)	*(1.034)*	(1.594)	*(1.589)*	(0.588)	*(0.590)*
log (stock)		*-0.051*		*0.776*		*-0.271*
		(0.540)		*(0.674)*		*(0.307)*
Intercept	12.237***	*12.457****	12.079***	*8.706***	12.937***	*14.116****
	(0.156)	*(2.351)*	(0.194)	*(2.933)*	(0.088)	*(1.337)*
Adj. R^2	0.238	0.220	0.053	0.061	0.195	0.191

Significance: *** 0.1%, ** 1%, * 5%, ~10%

Table 13. Spencer Gulf and West Coast Prawn economic performance v efficiency

	Full equity profits	Boat business profits	Gross margins
log (TE)	1.590	-0.716	1.713~
	(1.788)	(2.179)	(1.017)
log (UCU)	4.205**	2.365	1.880*
	(1.359)	(1.844)	(0.759)
log (AE)	1.445	-5.121	2.619
	(13.83)	(17.65)	(7.679)
log (CE)	-1.904	12.841	-3.253
	(11.43)	(14.15)	(6.453)
log (PE)	1.617	-6.022	1.038
	(4.910)	(5.983)	(2.700)
Intercept	12.377***	11.788***	13.001***
	(0.388)	(0.470)	(0.214)
Adj. R2	0.185	0.046	0.148

Significance: *** 0.1%, ** 1%, * 5%, ~ 10%

provides no further information.[12]

We also examine whether the value-based efficiency estimates give us any further explanation. Table 13 shows that adding the estimates of allocative, cost and profit efficiency are not strongly related to the direct economic measures. Only unbiased capacity utilisation retains statistical significance, the additional variables are not statistically significant, and overall power reduces.

Given the weak correlation between the physical efficiency estimates and economic performance, we now examine the economic information in more detail. Table 10 showed the mean of profit, revenue and catch but now we show in Figure 24, Figure 25 and Figure 26 the mean and interquartile range of our measures of profits, margins, costs, income and catch. These measures cover a longer time period than the efficiency metrics, and are all real values.[13]

As can be seen in Figure 24, there is large variation in the measures of profit, with lower means in the three middle years (2004/5, 2008/9 and 2012/3) and interquartile ranges of $200,000 or more. If we examine the costs, shown in Figure 25, we see increases in each of Boat Variable, Labour Variable, and Fixed Costs. Finally, observing the output measures in Figure 26, while catch (centre panel) is relatively stable, income and average price have both risen significantly and increased in variability. Returning to our earlier note that labour is typically paid with a crew-share of revenue, as income rises we might expect total labour costs to rise, even without labour quantity rising. There does, however, seem to be increased labour usage with mean full-time-equivalent rising from 2.9 to 3.9 to 4.4 across the three periods.

Together, this information suggests that while the physical outputs and inputs, and hence measures of technical efficiency and capacity utilisation are relatively homogenous within this fishery, the economic performance is much more heterogeneous. The much greater variation in economic outcomes than in quantities indicates the reason for the lack of correlation, we discuss the intuition for this below.

[12] The measure for stock was provided via personal request from SARDI Noell et al. (2021).

[13] Nominal data converted to real 2019 prices using the Australian CPI.

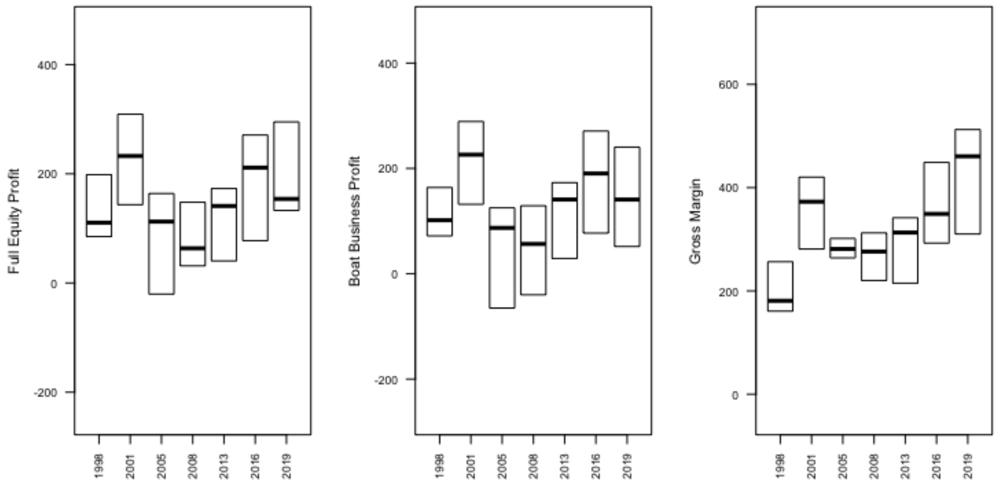


Figure 24. SGWCP profits ($000)

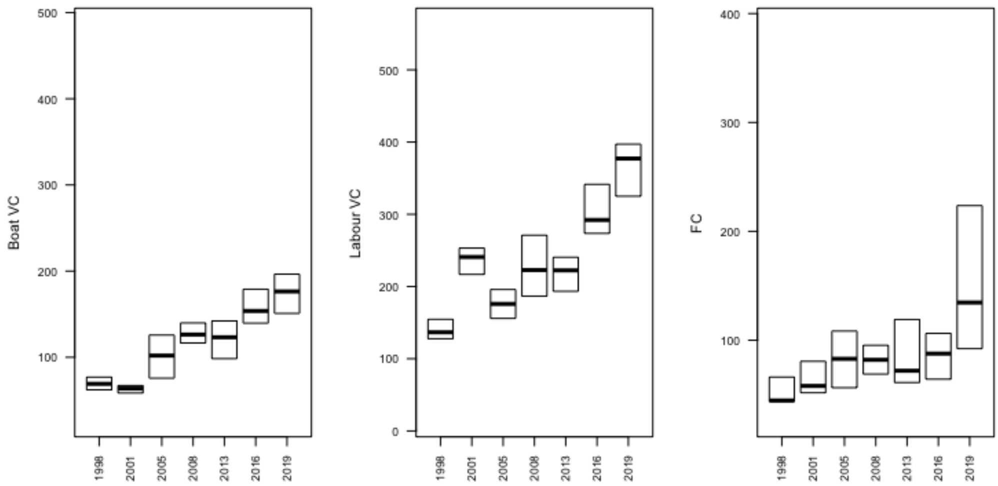


Figure 25. SGWCP costs ($000)

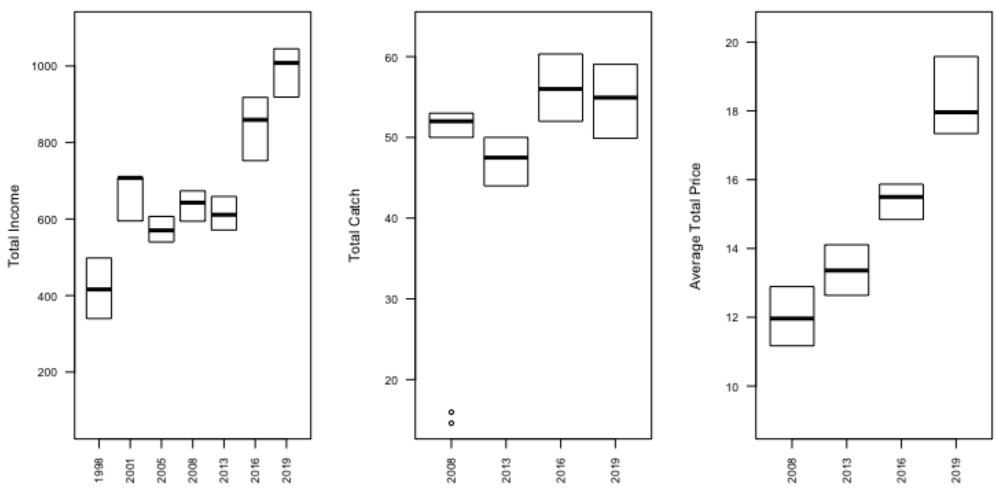


Figure 26. SGWCP income ($000), catch (tonnes) and price ($/kg)

Note: For each year, the bottom of the box (bar) indicates the 25th percentile, the dark midline indicates 50th percentile (median), the top of the box indicates the 75th percentile. The whiskers (that would usually show minimum and maximum) are omitted for confidentiality.

Spencer Gulf and West Coast Prawn Fishery discussion

The Spencer Gulf and West Coast Prawn Fishery (SGWCPF) is a small, input-controlled fishery with detailed value-based (cost and revenue) information collected from voluntary surveys conducted every three to five years since 1998. The collection of quantity-based data in this fishery is more recent. The results of our analysis indicate that technical efficiency and capacity utilisation are relatively high in this fishery. The relationship between these quantity measures and the economic measures of performance are, however, not strong.

The input restrictions and cooperative management approach taken means that the quantities of inputs employed and outputs are relatively homogeneous. More skilled or experienced fishers may catch more for the same labour, but boat size and nights fished are relatively constant. Examining the economic metrics in more detail indicates a greater variation in costs (both variable and fixed) and in average total price received for the harvest. It is natural that when faced with input restrictions and similar catch, the key levers remaining to improve economic outcomes for an individual must necessarily come via the input and output price mechanisms. The more successful fishers are those that use their skills to find market outlets that pay higher prices. Hence, for this fishery, quantity-based measures are unlikely to be appropriate indicators for economic outcomes.

The SGWCPF is similar to the Commonwealth Northern Prawn Fishery in being an input-controlled prawn fishery and having quantity and value information for inputs and outputs for a subset of the fleet. It is, however, not a large fishery, the time horizon of the available data is considerably shorter, and we are unable to track individuals over time. The advantage of the larger, panel data for the NPF is that it allowed for: inclusion of individual effects leading to greater predictive power from the efficiency measures to the economic measures; and stochastic frontier analysis. The three-period analysis here, with a single area, precluded consideration of external factors such as environment, stock levels or management change (if any had occurred) as these would be the same for all observations in each of the three years, hence not allowing enough variation for the empirical analysis to give meaningful interpretation.

The type of results available serves to highlight that appropriate data collection does need to consider the objectives of the fishery and the management scenario. For instance, the SGWCPF has an economic component to the stated policy objectives, but is managed using input-controls. Hence the mechanism by which individuals can improve their economic outcomes is only through raising output prices or lowering input prices, rather than by changing quantities. The implementation of management in this fishery has lead to lower variation in quantities than in values, which has potential implications for longer-term pressures on cooperation in the fishery.

Queensland Spanner Crab Fishery Case Study

This case study focusses on the Queensland Spanner Crab Fishery. For this fishery only five variables, including catch and effort information, were available to assess the economic performance of the fleet. However, the data includes an extensive time series for all five variables (i.e., monthly data for 32 years), which allows an analysis in efficiency measures over time. Furthermore, spatial information about regions in which individual vessels fished was available. This offers the opportunity to undertake a combined spatial and temporal efficiency performance analysis of the spanner crab fleet. Overall, we show how the derived efficiency indicators in combination with the available data can be used to assess the impact of changes in fishery management on the economic performance of the fishery.

Spanner Crab Fishery introduction

Spanner crabs are marine decapod crustaceans found in the Indo-Pacific region (Kennelly 2019). In Australia, spanner crabs inhabit coastal waters along the east coast and typically populate in sandy habitats in depths of 10-60 metres (Skinner and Hill 1987, Sumpton et al. 1995, Brown et al. 1999). This crab species is thought to mature at about 4-6 years of age (State of Queensland 2020), spawn between October and February (with peak during late November to late December) and can reach an age up to 15 years (Brown et al. 1999). Males grow to about 150 mm rostral carapace length (RCL) and females to approximately 120 mm RCL and weigh approximately 900 grams (Brown et al. 1999).[14] Spanner crabs can be distinguished from other crab species by their red carapace and elongated round body.

Spanner crabs are commercially caught in Australian coastal waters ranging from Yeppoon in QLD to Yamba in northern New South Wales (Brown et al. 1999, Dichmont and Brown 2010, State of Queensland 2020). While this crab species also occurs north of Perth, Western Australia, no commercial harvest of spanner crabs takes place in that state. About 88% of Australia's commercial spanner crab catch is caught in QLD waters (FRDC 2020). Recreational (including charter) and indigenous spanner crab fishing is also permitted in QLD, however, 99% of spanner crab harvest occurs by the commercial fishery (single-species fishery) (FRDC 2020, State of Queensland 2020). Fishing methods include nets (mostly in NSW), traps, and dillies (i.e., framed nets) that are placed on the sea floor (Sumpton et al. 1995, FRDC 2020, State of Queensland 2020).

The spanner crab fishery is managed by QLD DAF, which determines fishing areas, conducts stock assessments, and sets input and output restrictions. The QLD spanner crab fishery currently extends over two separate management areas (area C2 and area C3), which are divided by latitude 23 south near Yeppoon (State of Queensland (2020), see Figure 27). Most of the catch from the fishery occurs in management area C2 (southern QLD segment of the fishery), which is further divided into five fishing regions for the purpose of monitoring and assessment, and include (from north to south) the town of Seventeen Seventy (identified as '1770' in the remainder of this study), Bundaberg, Tin Can Bay, Stradbroke and Gold Coast (State of Queensland 2020, State of Queensland 2020) (Figure 27). These five fishing regions within management area C2 will be the focus of this study.

During the 1970s to 1990s the QLD spanner crab fishery expanded significantly in regard to catch volume with its peak in 1994 when a total catch of over 3,500 tonnes was recorded (see Figure 28) (Brown et al. 1999). The *Fisheries (Spanner Crab) Management Plan 1999* introduced a range of input and output controls, for example, gear restrictions, decrease in fishing licences, temporal closures, and total allowable catch (TACC, with latest reduction in TACC in 2018) managed through individual transferable quotas (ITQs) in management area A (State of Queensland 2001). These were gradually refined over time (State of Queensland 2008, State of Queensland 2019, State of Queensland 2020). The suite of management interventions has contributed to achieving a sustainable stock status in 2020 (FRDC 2020).

[14] Rostum is the front section (e.g., head, nose) and carapace is a dorsal section of the exoskeleton or shell of the crab. Both are used to determine aquatic animal rostral carapace length measurement.

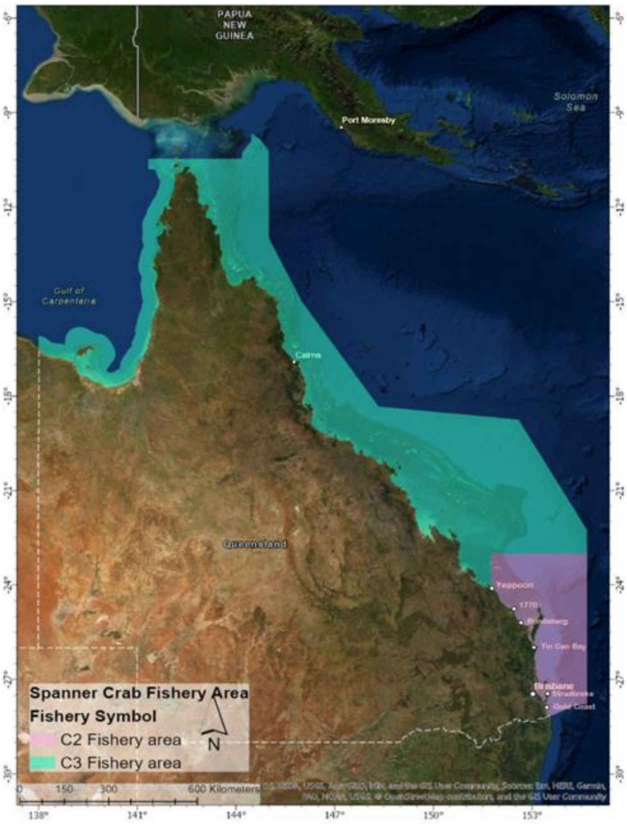


Figure 27. Spanner crab management areas in Queensland

Source: State of Queensland (2020). Notes: The C2 fishing area corresponds with management area where most commercial spanner crab fishing occurs. The C3 spanner crab fishing area is not considered in this study due to limited commercial catch. Fishing area C1 is not mapped here since it includes all crabs other than spanner crabs, i.e., mud crabs and blue swimmer crabs, which are not relevant for this study.

A formal harvest strategy has more recently been implemented for the commercial spanner crab, which sets out decision rules to determine appropriate levels of harvest based on the status of spanner crab stocks with the aim to rebuild depleted stocks (State of Queensland 2020). The aim of the harvest strategy is to set catch at levels appropriate for rebuilding to the 60% biomass target, minimising the risk of a full fishery closure and maintaining catch shares amongst commercial and recreational sectors (State of Queensland 2020). Since no modelled stock assessment is available for spanner crabs, the stock is assessed on the basis for the performance of the fishery using commercial fisher catch per unit effort (CPUE) (annual standardised catch rate) (O'Neill et al. 2010) and fishery independent survey data (catch rate of legal-size crabs) to infer the status of the stock (State of Queensland 2020). Commercial logbooks, prior landing reports and buyers logbooks are used to monitor the catch volume and compulsory vessel tracking units are used to validate fishery operations (State of Queensland 2020).

Although there is a collaboration agreement between NSW and QLD, both jurisdictions have separate management arrangements for their portion of the stock NSW DPI (2020). The management of the QLD spanner crab fishery is not directed by formal economic objectives, however there are economic objectives outlined in the harvest strategy that are “intended to provide some guidance on options that could resonantly be considered if fishery trend are of concern” (State of Queensland 2020).

There are currently (2020) only 36 active licences operating in the spanner crab fishery (see dashed line in Figure 28). The combined total production value generated by the fleet is about A$8.0-A$9.3

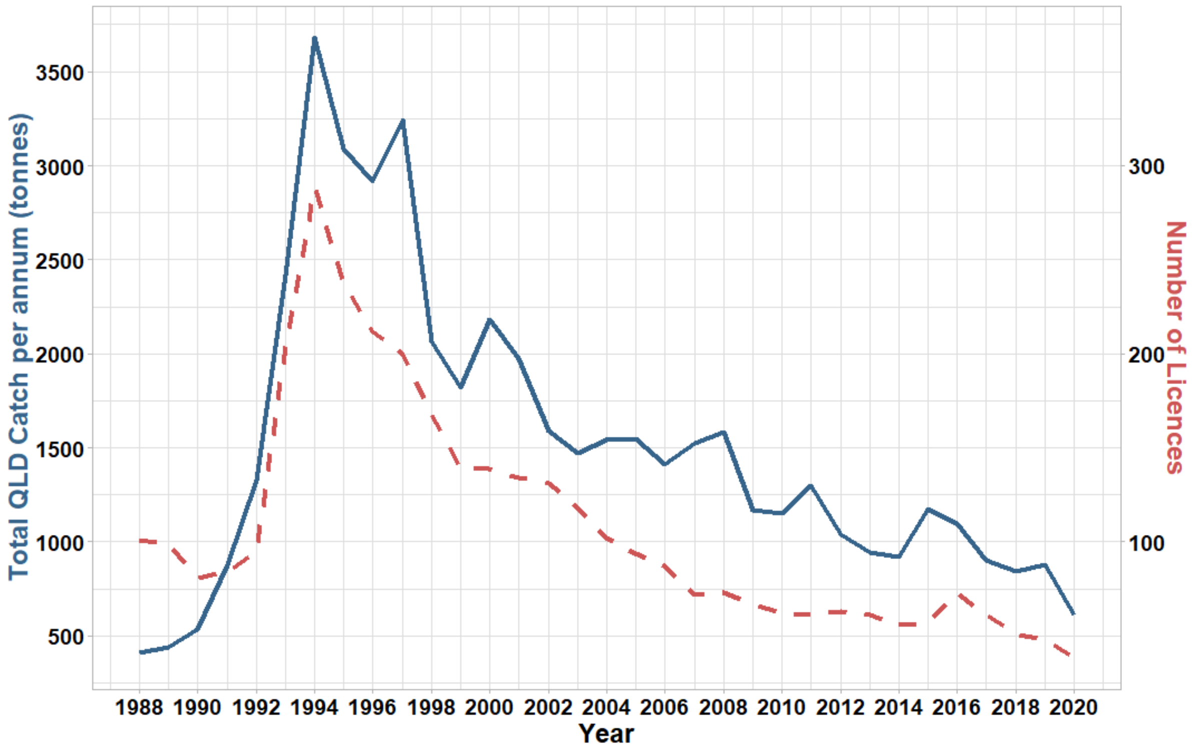


Figure 28. Total QLD spanner crab catch per annum and number of licences over time

Source: State of Queensland (2020)

million per annum (BDO EconSearch 2020). This translates into an ex-vessel average unit price of about A$9.30-A$9.40 per crab (BDO EconSearch 2020). As such, the spanner crab fishery presently only contributes a relatively small economic value annually to QLD's economy compared to the East Coast Trawl Fishery (A$109.8 million), Coral Reef Fin Fish Fishery (A$33.4 million) or the East Coast Mud Crab Fishery (A$26.0 million) (BDO EconSearch 2020). However, it is estimated that the spanner crab fishery directly employs about 156 people in QLD (BDO EconSearch 2020). Hence, the fishery has a socio-economic importance for coastal communities in south-east QLD which rely on the income generated from this commercial fleet.

As a seafood product, spanner crabs are caught for their meat, are sold mostly to the domestic market (BDO EconSearch 2020) and are considered as a low-medium priced seafood product (SFM 2021). At the domestic wholesale market, spanner crabs are sold at about A$25.00-A$29.50/kg (whole raw spanner crab) (GCFC 2021, Scales Seafood 2021). Only a small proportion of the catch is exported which generates a value of approximately A$0.3 million per annum (BDO EconSearch 2020).

Assessing the relationship between production inputs and outputs of this small-scale fishery may assist fishery managers to determine the extent and means by which its economic productivity can be enhanced.

Method, data, and benchmarking approaches

Method

In this study DEA, as described in the Case Study Methodology, is used to assess the relative performance of vessels operating within the five commercial spanner crab fishery regions in Queensland over time. The efficiency measures to be estimated for this case study are TE, CU, UCU and SE.

Data

Data for the analysis were made available from QLD DAF. A total of 20,622 observations were recorded after data cleaning (e.g., removal of observations with missing variables and extreme outliers) which includes monthly data ranging from January 1988 to December 2020. The data set comprised de-identified individual vessel time series data for production input variables such as the number of days per month fished, number of dillies set, number of dillies lifted (i.e., checked), engine power in kilowatt, fishing region (i.e., Town of 1770, Bundaberg, Tin Can Bay, Stradbroke, Gold Coast, see Figure 27), and production output (i.e., catch volume in kilogram). A previous study by O'Neill et al. (2010) described the spanner crab fleet characteristics using additional variables such as skipper experience, crew number, fuel use per day and some of these variable were collected for 2019 and 2020. However, such a data set was not available for individual vessels and over time (1988-2018) or could not be made available for this analysis (2019-2020).

The descriptive statistics of the full sample and sub-samples (reasons for subsample splits are provided further below) for input and output variables are presented in Table 14. The descriptive statistics show that observations for fishing region in the north of management area A (i.e., Town of 1770, Bundaberg and Tin Can Bay) recorded a higher output over time and more input units compared to the southern fishing regions (i.e., Stradbroke, Gold Coast). Furthermore, there also appears to be large variation for specific variables (e.g., engine power, output) within each sub-sample.

The plotted means of input and output variables in Figure 29 provide more detail about their dynamics. While the days fished decreased, the number of dillies set increased from 45 to 75 which reflects further changes to the fishery management from 2008 (e.g., general fishing permits allowed individual spanner crab fishers to use more than the 45 dillies stipulated in the Fisheries Regulation 2008 (State of Queensland 2008, Australian Government 2012). The hull units increased with time (i.e., larger vessels) and so did the engine power. The number of dillies lifted increased in some regions while it decreased in others. The average catch decreased during the 2000s compared to the 1990s and remained approximately the same thereafter. It should also be considered that the number of licences for vessels operating in this fishery reduced significantly over time (see Figure 28).

Prior to conducting the detailed fleet performance assessment, the correlation between input and output variables were tested using the full sample (1988-2020) to ensure isotopic relationships. This means if inputs increase, outputs should not decrease (Wang et al. 2021). The correlation matrix of the variables shown in Table 15 indicates that the Pearson correlation coefficient, a measure of any linear trend between two variables, is relatively low (e.g., less than 0.5) and positive for all pairs, except days fished/dillies lifted and days fished/output for which a relatively strong positive relationship was identified. This suggests that there is only a small linear association among most variables, while two variables are strongly linear associated, and these relationships are to some degree expected. Dyson et al. (2001) show that omission of variables in DEA purely on grounds of correlation should be avoided since correlation is an aggregate measure of the closeness of two sets of observed data (e.g., two inputs) and variation of the input level of individual observations may have little effect on the correlation but a significant effect on measured efficiency. Hence, all six variables (see Table 14, Table 15) were considered in the analysis.

Benchmarking approaches

To reflect the major changes in fishery management following the introduction of the *Fisheries (Spanner Crab) Management Plan 1999* (e.g., gear restrictions such as number of dillies permitted to be used and net specifications, commencement of TACC) (State of Queensland 2001) two time periods are considered to assess potential differences in efficiency measures prior to and post these regulatory changes. This is important since input and output controls imposed by the management authority can influence the economic productivity of vessels (Greenville et al. 2006).

Hence, the first period includes production years ranging from 1988-1999 ('Before 2000'). The second period focuses on the years 2000-2020 ('After 1999') (see Table 16). An important assumption for the

Table 14. Descriptive sample statistics (1988-2020)

Sample	Observations	Statistic	Inputs					Output
			Days fished	Dillies set	Dillies lifted	Hull units	Engine power	
Full sample	20,622 [1988-2020]	Median	4.00	45.00	2.00	5.70	187.00	783.90
		Mean	5.25	47.86	2.83	8.06	199.40	1,449.09
		St. dev.	4.44	19.81	2.08	8.46	100.92	1,986.79
Town of 1770	2,586 [1988-2020]	Median	4.00	45.00	2.00	6.90	231.00	994.60
		Mean	4.76	48.37	2.84	8.26	222.18	1,541.56
		St. dev.	3.96	17.21	2.18	5.84	85.21	1,587.16
	654 [1988-1999]	Median	4.00	30.00	2.00	6.00	179.00	1,146.70
		Mean	5.56	30.60	3.31	8.18	201.57	1,527.92
		St. dev.	4.42	7.09	2.72	5.95	87.40	1,407.57
	1,932 [2000-2020]	Median	3.00	45.00	2.00	6.90	238.00	950.00
		Mean	4.49	54.38	2.68	8.29	229.16	1,546.18
		St. dev.	3.75	15.38	1.93	5.80	83.34	1,643.83
Bundaberg	3,410 [1988-2020]	Median	5.00	45.00	2.00	8.30	240.00	1,200.00
		Mean	6.23	45.57	3.10	9.81	229.49	2,038.11
		St. dev.	5.47	18.30	2.42	6.71	91.05	2,370.57
	1,084 [1988-1999]	Median	6.00	30.00	3.00	8.20	194.00	1,490.00
		Mean	7.87	29.29	3.78	10.00	202.52	2,409.13
		St. dev.	6.41	9.14	3.05	6.71	86.27	2,776.44
	2,326 [2000-2020]	Median	4.00	45.00	2.00	8.30	270.00	1,062.50
		Mean	5.47	51.69	2.78	9.71	242.05	1,832.41
		St. dev.	4.79	17.11	1.99	6.70	90.51	2,037.38
Tin Can Bay	6,831 [1988-2020]	Median	4.00	45.00	2.00	6.90	210.00	1,015.00
		Mean	5.36	52.12	2.92	9.90	209.19	1,818.29
		St. dev.	4.28	23.06	2.10	10.90	108.55	2,543.81
	1,223 [1988-1999]	Median	3.00	30.00	2.00	6.40	168.00	668.60
		Mean	4.51	27.84	2.73	7.07	194.47	1,058.73
		St. dev.	3.73	9.03	2.02	6.68	106.56	1,151.13
	5,608 [2000-2020]	Median	4.00	45.00	2.00	6.90	210.00	1,110.00
		Mean	5.54	57.41	2.96	10.52	212.40	1,983.93
		St. dev.	4.37	21.76	2.12	11.53	108.72	2,727.69
Stradbroke	4,934 [1988-2020]	Median	3.00	45.00	2.00	3.70	150.00	470.00
		Mean	4.49	45.09	2.60	6.12	177.53	777.91
		St. dev.	3.76	17.47	1.89	7.05	96.07	842.09
	1,225 [1988-1999]	Median	5.00	30.00	3.00	2.70	149.00	689.00
		Mean	5.68	30.24	3.14	4.72	151.27	987.41
		St. dev.	4.17	8.16	2.14	4.62	85.99	947.41
	3,709 [2000-2020]	Median	3.00	45.00	2.00	3.80	168.00	420.00
		Mean	4.10	49.99	2.43	6.58	186.20	708.72
		St. dev.	3.53	16.95	1.77	7.62	97.65	792.35
Gold Coast	2,861 [1988-2020]	Median	4.00	45.00	2.00	2.70	149.00	548.30
		Mean	5.55	46.94	2.70	4.73	157.31	966.11
		St. dev.	4.68	17.07	1.73	5.71	92.51	1,183.84
	581 [1988-1999]	Median	4.00	30.00	3.00	2.30	149.00	560.00
		Mean	5.96	29.21	2.92	2.50	130.80	887.28
		St. dev.	1.07	7.11	1.84	1.87	59.36	943.67
	2,280 [2000-2020]	Median	4.00	45.00	2.00	3.20	149.00	540.00
		Mean	5.45	50.20	2.65	5.30	164.07	986.20
		St. dev.	4.57	16.23	1.70	6.20	98.07	1,236.99

Source: State of Queensland (2020). Notes: Hull units (HU) were calculated based on HU = (L x B X D x 0.6) / 2.83, with L for length, B for beam, and D for depth of the vessel. The factor 0.6 represents a block coefficient to standardise variations in boat design and the factor of 2.83 represents a constant which converts cubic metres to units of 100 cubic feet.

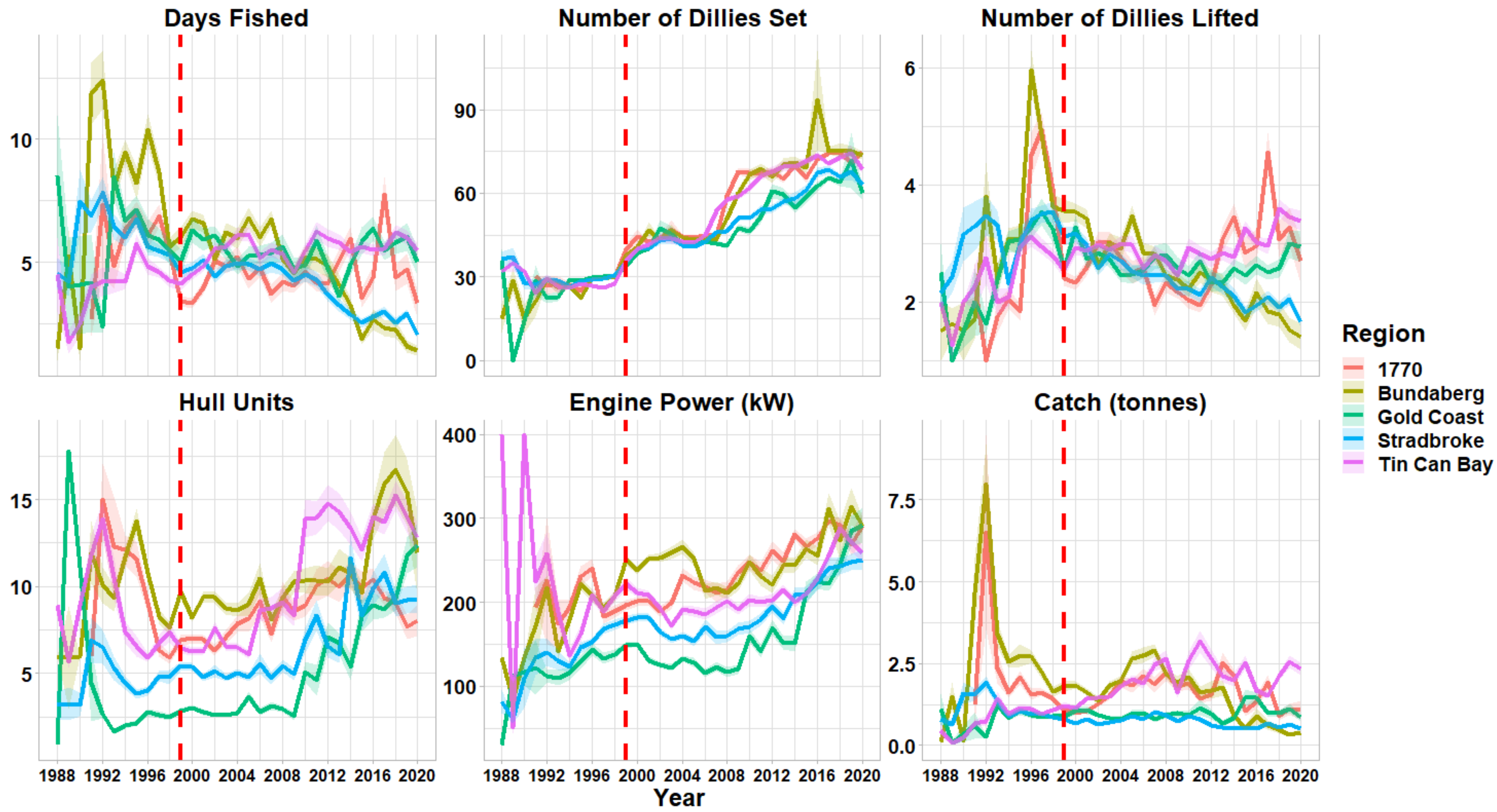


Figure 29. Mean of input and output variables over time

Notes: Standard error of the mean is shown as shaded area around mean for each fishing region. Red dotted line identifies the year 1999, when significant fishery management changes were introduced. Data cleaning explains differences in catch (tonnes) shown above compared to statistics in Table 14

Table 15. Correlation matrix using Pearson correlation coefficients (full sample: 1988-2020)

Variables	Effort	Dillies set	Dillies lifted	Hull units	Engine power	Output
Effort	1.000	0.063	0.734	0.122	0.089	0.741
Dillies set	0.063	1.000	0.076	0.465	0.314	0.257
Dillies lifted	0.734	0.076	1.000	0.107	0.112	0.515
Hull units	0.122	0.465	0.107	1.000	0.464	0.333
Engine power	0.089	0.314	0.112	0.464	1.000	0.205
Output	0.741	0.257	0.515	0.333	0.205	1.000

Source: Estimates were derived using data provided by State of Queensland (2020).

first period is that only the inputs hull size and engine power are considered as fixed, while dillies set, effort and dillies lifted were considered as variable inputs to derive the output. Yet, for the second period (2000-2020) the variable dillies set was treated as fixed input to reflect the implementation of this restriction according to the *Fisheries (Spanner Crab) Management Plan 1999* (State of Queensland 2001). Given the TACC and ITQs, introduced in 1999 (State of Queensland 2020, State of Queensland 2020), are set based on regular CPUE assessments, which provides an indicator of stock health, it was assumed for 2000-2020 that the fleet operated within sustainable yield limits, notwithstanding the need for a significant reduction in TACC in 2018 in response to declining stock status (State of Queensland 2022).

The efficiency frontier was estimated across both periods on an annual basis (32 years) and includes all five regions. This benchmarking approach also accounts for changes in the TAC and ITQs over time. Hence, this procedure identifies the most efficient vessel of the fleet in a specific year against which the performance of all other vessels operating in the respective fishing regions were compared.

To assess differences in the derived mean scores for all productivity measures between the period before 1999 and after 2000, a Student's t-test was undertaken assuming unequal variances. The t-test was further adjusted for multiple comparisons using the Benjamini and Hochberg correction method (Benjamini and Hochberg 1995, Benjamini and Hochberg 2000).

To determine the effect of re-assigning dillies set from a variable input in the period before 2000 to a fixed input in the period after 1999, the full data set (covering the entire time series from 1988 to 2020) was analysed using both benchmarking approaches (Table 16) and the statistical relationship among the pairs of efficiency scores from these two approaches were tested with a bivariate Pearson correlation analysis.

Table 16. Benchmarking approaches for different time periods

Assumptions	Period 1: Before 2000	Period 2: After 1999
Time period focus	1988-1999	2000-2020
Fixed inputs	Engine power, hull size	Dillies set, engine power, hull size
Variable inputs	Dillies set, effort, dillies lifted	Effort, dillies lifted
Output	Output	Output
Fishing regions	All five regions	All five regions
Implicit considerations	Limited input and output controls implemented	Considerable input and output controls implemented

Results and discussion

The derived scores of the four efficiency measures are presented in Figure 30 and Figure 31. The results in Figure 30 show that the aggregated mean scores for the TE of vessels operating in the five different fishing regions were relatively variable across years and regions in the period before 2000 (1988-1999) compared to the mean scores derived for period after 1999 (2000-2020). This result is likely an effect of the limited annual observations during 1988-1993 (e.g., 17-132). This effect has also been observed for results of the other efficiency measures (Figure 30). The outcomes in Figure 31 (panel A, blue diamonds) show that the aggregated mean TE scores for each time period were relatively low, ranging between 0.30-0.51. In comparison, vessels on the production frontier have a technical efficiency score of 1.00. The aggregated mean TE scores have slightly decreased in the period after 1999 compared to before 2000 (Figure 31, panel A). The decrease in TE scores across both periods was statistically significant as indicated by the p-value of the Student's t-test for all five fishing regions (present on top of the respective boxplots in Figure 31, panel A).

Interestingly, the boxplot for the region Stradbroke in Figure 31 (panel A), supported by the blue line graph in Figure 30, suggests that vessels operating in this region had the least technical efficiency during 2000-2020, although the region's TE scores improved in recent years. In contrast, vessels catching spanner crabs in Tin Can Bay appear to have had slightly higher TE scores in the period after 1999 compared to vessels fishing in the other regions (Figure 30, Figure 31 panel A). The findings about TE scores for Stradbroke and Tin Can Bay align well with each region's trends in variable inputs (i.e., days fishes, dillies lifted) as shown in Figure 29.

The derived aggregated mean scores for CU were very low across all fishing regions and statistically different across each time period (Figure 31, panel B), except for the fishing region 1770, where CU scores have not changed between before and after 2000. The CU scores across all regions ranged between 0.14-0.25 (Figure 31, panel B). The more detailed results for CU in Figure 30 confirm that there was very limited fluctuation in the scores after 1994 -2020, while the high variation in the CU mean scores during 1988-1993 is, as before for TE, likely due to the limited number of observations in the data set for this period.

The results for the bias adjusted UCU measure reveal slightly higher scores than the CU scores across time and for all regions, ranging between 0.34-0.52 (Figure 31, panel C). The p-values for the t-test suggest that the aggregated scores across the two time periods were not significantly different for the regions 1770, Bundaberg and Gold Coast. Notable in Figure 30 is that the CU and UCU scores for the Bundaberg region have more recently fallen (2000-2020) below the scores of other regions, which is not observable from the results in Figure 31 (panel B and panel C) due to the aggregation of mean scores across time periods. Overall, the derived results for UC and UCU suggest that fixed inputs such as hull units, engine power and dillies set (only during 2000-2021) remain relatively poorly utilised by vessels operating in this fishery.

The outcome of the analysis also shows that the aggregated mean scores for SE were very high during 1988-1999 in all fishing regions ranging from 0.82-0.93 (Figure 31, panel D). The SE scores slightly decreased during 2000-2020 across all regions fluctuating between 0.72-0.84 (Figure 31, panel D). Figure 30 shows that the decrease in SE scores specifically occurred from 2006. This suggests that the fleet has moved further away from its optimal production scale which equals a score of 1. Put differently, the output of the fleet during 2000-2020 could have further increased (under given TAC and ITC constraints that applied during this period) by about 15-28% if it had reached its most productive size.

Although only relatively small differences in scores of efficiency measures between the two periods were found in our anaysis (Figure 30, Figure 31), we tested if these differences actually resulted from the treatment of dillies set in the benchmarking approach (see Table 16) or from other influences. Figure 32 shows the results from a correlation analysis in which a comparison of the scenario A (i.e., analysis for all efficiency measure is run with dillies set as variable inputs across the entire time series,

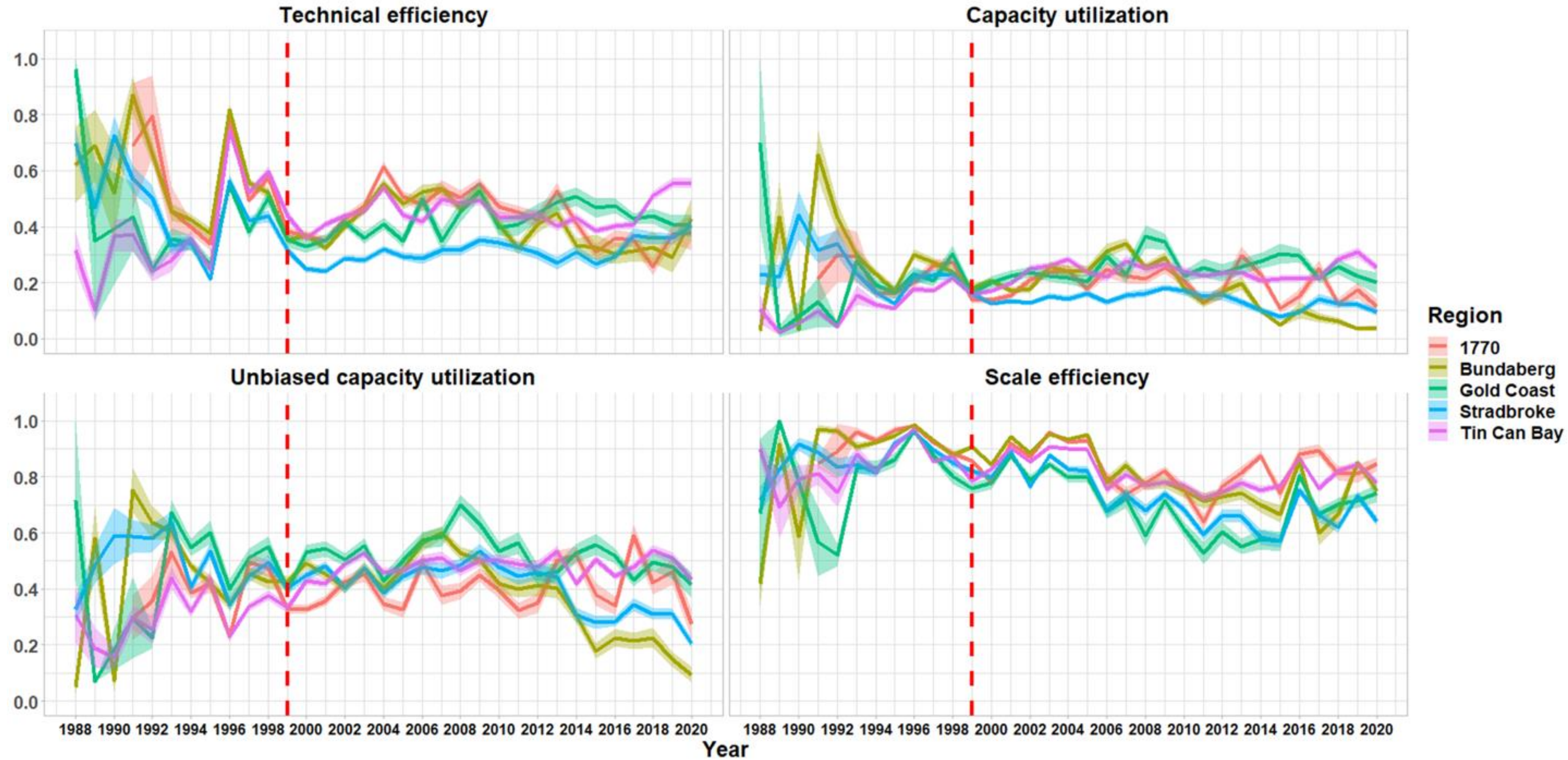


Figure 30. Mean scores (with shaded standard errors) of efficiency measures for Queensland Spanner Crab

Notes: Standard error of the mean score is shown as shaded area around mean for each fishing region. Red dotted line identifies the year 1999, when significant fishery management changes were introduced.

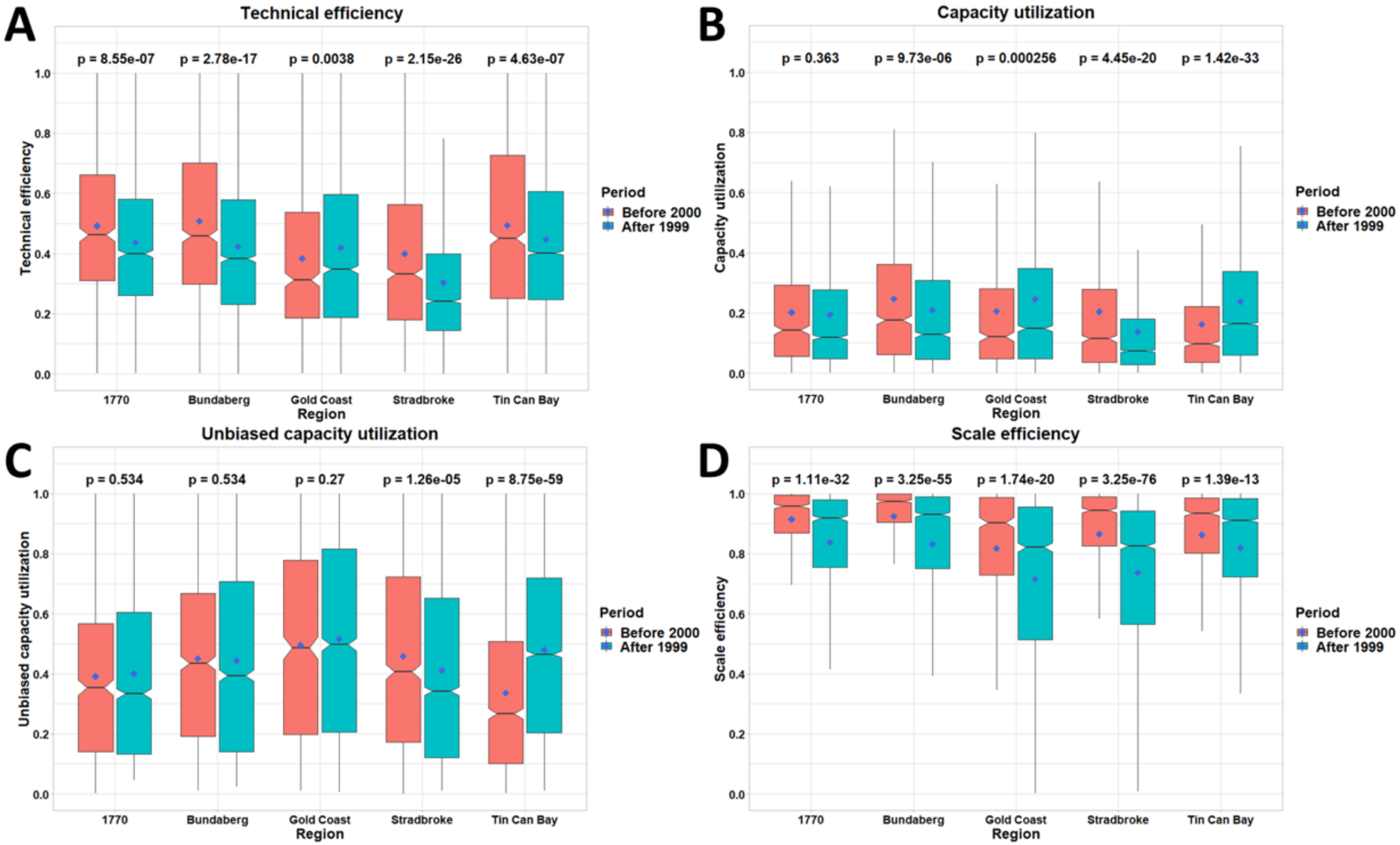
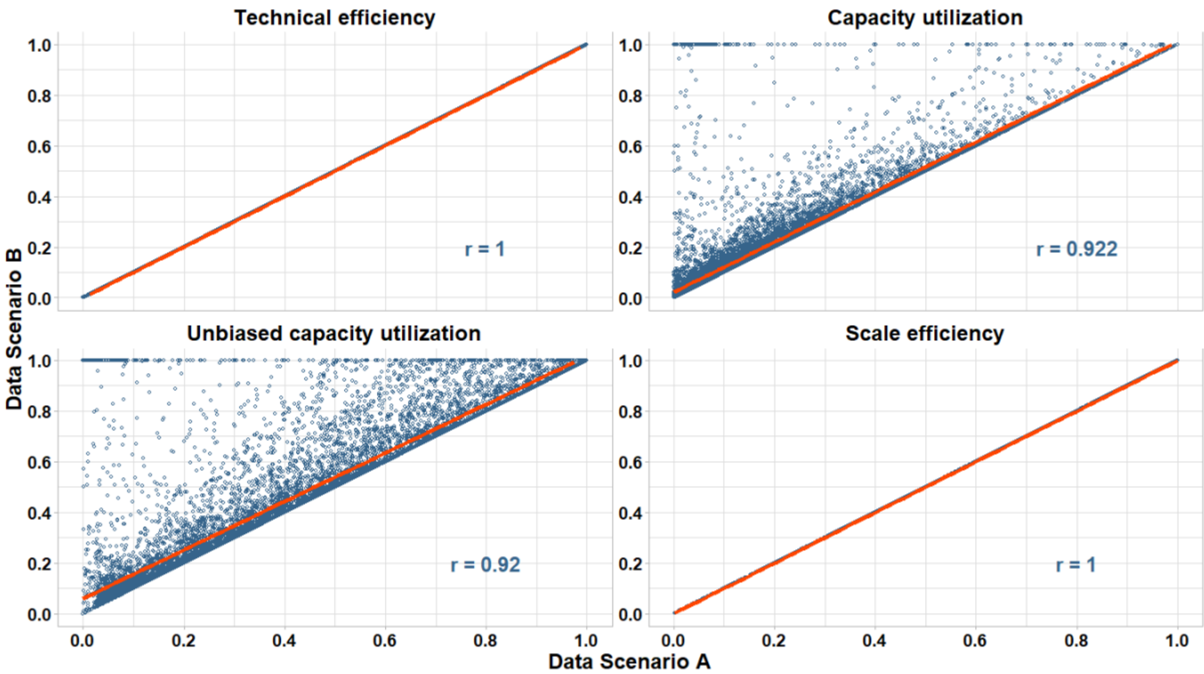


Figure 31. Comparison of aggregated average scores of efficiency measures across periods and region

*Notes: The height of the box indicates first and third quartiles (the 25th and 75th percentiles), the midline indicates 50th percentile (median). Whiskers of the boxplot signify the smallest and largest scores that are greater/equal to or less/equal to 1.5*Interquartile range, respectively. A blue diamond indicates the aggregated group mean scores for respective fishing regions.. A blue diamond indicates the aggregated group mean score for respective fishing regions. The p-value was calculated using an unpaired Student's t-test assuming unequal variance and adjusted for multiple comparisons by controlling the false discovery rate after Benjamini and Hochberg (1995, 2000). It compares the aggregated group mean scores for respective fishing regions across both periods.*



Notes: r is the Pearson correlation coefficient.

Figure 32. Pearson's correlation coefficient for comparison of scenario A and B

1888-2020, and all fishing regions) with scenario B (i.e., analysis is run with dillies set as fixed input). Data derived from scenario A and scenario B where identical for TE and SE and highly correlated for CU and UCU as indicated by the Pearson correlation coefficient (r) of 1.00 for TE and SE and 0.92 for CU and UCU (Figure 32). This result suggests that there are only negligible differences in the estimated efficencies scores based on the treatment of dillies set as variable or fixed input.

Queensland Spanner Crab discussion

The results of this study suggest that the change in fishery management, represented by the treatment of dillies set as an input of our analysis, was unlikely to have impacted the efficiciency and productivity of the spanner crab fleet over time and fishing regions (Figure 30, Figure 31).

However, the results revealed that the TE of the spanner crab fleet has been relatively low over time and across all five fishing areas. This implies that the use of variable inputs across the entire fleet has been relatively inefficient compared to the most technical efficient vessels (production frontier). Similar was found for CU and UCU, which means that there is a large proportion of excess capacity present within the fishery. This suggests a potential overinvestment into fixed inputs, e.g., boat size (hull units) and engine power. Overall, these results mean that the economic performance of the fishery is relatively inefficient and underutilised. This finding could be due to the presence of a large proportion of part-time/hobby fishers who were operating in the commercial spanner crab fleet. Such findings were also reported for the Sydney rock oyster fishery in Australia (Schrobback et al. 2015). However, further data and analysis to verify this is needed.

The results also suggest that the significant TACC reduction in 2018 (State of Queensland 2022) may not have provided a large incentive for inefficient vessels to leave the fleet. This can be seen from the TE scores in Figure 30 which remain about the same as prior 2018, while CU and UCU scores appear to decrease further after 2018. This may change over time as adjustments in fixed inputs depends on fishers' ability to reduce their overinvestment in capital (e.g., access to financial capital to invest in smaller vessels).

While the reduction of TE and SE since 2000 (Figure 31) cannot be attributed to how the changes in management was considered in this study (Figure 32), it is likely that other management changes (e.g., subsequent fishery input regulations (State of Queensland 2008, State of Queensland 2019) may have influenced the decreasing trend in TE and SE scores. For example, the average number of dillies set within the fishery sharply increased in 2008 (see Figure 29). This is likely due to general fishing permits allowing individual fishers in the spanner crab fishery to use more than the 45 dillies stipulated in the Fisheries Regulation 2008 (State of Queensland 2008, Australian Government 2012).

The changes to permit regulations may have subsequently caused the increase in hull size and engine power of vessels (fixed inputs), while the average output decreased slightly (likely due to decrease in TACC and licences) (Figure 29). Such dynamics could be an explanation for the decrease in SE which commenced around the same time (Figure 30).

Furthermore, other factors (e.g., changes to input price skipper's experience, age) may have influenced the scores of all four efficiency measures (e.g., Squires and Kirkley 1999, Schrobback et al. 2015, Mkuna and Baiyegunhi 2021). For example, the region Stradbroke returned continuously low scores for TE and CU (Figure 30) which is likely due to a lower use of inputs (e.g., less days fished, low hull units and engine power) compared to other regions. Yet, reasons that could explain skippers' choices for the relatively low inputs remain unexplained. Data about fisher characteristics (e.g., age, fishing strategy) (e.g., Schrobback et al. 2015), fishing costs (e.g., Madau et al. 2018) or the relative spatial stock abundance in a fishing region can be useful in explaining these efficiency scores (e.g., Jin et al. 2002). Hence, the absence of data for such variables limits a further investigation into the potential causes for low TE, CU, and UCU scores across time and fishing regions.

The results from this study are similar to findings by Kompas et al. (2004) who identified a gap between actual and optimal economic performance levels of Australia's banana prawn fishery. A challenge that these authors identified as contributing to this situation include insufficient prioritisation of economic objectives in the management of the fisheries.

While the spanner crab fishery is already tightly managed through a range of output and input controls with focus on the ecological sustainability of the fleet, the management of its economic performance appears to be limited. This can be concluded since the identified inefficiencies that occurred over time (i.e., TE, CU) have not been addressed earlier by the fishery's management. Hence, the development of clear economic objectives (e.g., maximum economic yield, technical efficient use of inputs, economic profitability of the fleet, continued employment as described in Hilborn (2007)) are needed as a basis to increase the economic performance of the fleet which requires vessels to be both efficient and fully utilised. However, the development of the economic objectives needs to be made in consideration of biological, ecological, social and governance objectives of the fishery (Ogier et al. 2020). This will require further research, including stakeholder engagements.

The identified data gaps should also be addressed by the fishery management through regular collection of information for variables such as annual vessel revenue, profit, operation costs, labour use, and fisher characteristics (e.g., skipper experience, education, age, fishing strategy) and spatial stock abundance. Such data could be used to refine the analysis as a basis for fishery management decisions that focus on the improvement of the economic performance of the fleet. Understanding the level, distribution, and drivers of efficiency in a fishery on an ongoing basis is fundamental for achieving maximum economic yield objective.

Although the dataset used for analysis only offers a limited number of variables (see Table 14), the relatively long time series and spatial data about vessel movements provides scope for further assessment. For example, closer examination of individual vessel dynamics could help understand whether there are any behavioural aspects that may explain the economic performance of the fleet.

Queensland Spanner Crab summary

The aim of this case study was to assess potential temporal and spatial differences in productivity measures of vessles operating in the Queensland spanner crab fishery. This included an analysis of the impact of fishery management changes on productivity measures.

Assuming that the efficiency measured reflect the economic performance of the fleet, the results suggest that the changes in the management of the fishery did not affect the economic performance. However, the findings showed that the fleet has been operating relatively technically inefficient and with underutilised capacity over time and across all five fishing regions. The scale efficiency was high historically but decreased slightly since 2006 for all regions. Yet, this decline is likely not caused by the fishery management changes as considered in this analysis but due to other factors.

Additional data (e.g., revenue, profit, costs, skipper experience) and analysis is needed to assess the causes for the low technial efficiency and capacity utilisation over time and the decrease in scale efficiency in more recent years. While such data has been collected in 2019 and 2020, continued collection of such information and its assessment should be considered by the fishery's management.

Furthermore, the development of clear economic objectives and the monitoring of the fleet's economic performance should be prioritised by the management authority to ensure a balance between maximum economic yield and ecological sustainability of the spanner crab fishery.

Moreover, clear and coherent economic fishery management objectives (e.g., viability and efficiency of commercial fishers, maximising net economic returns) need to be developed that align with the fishery's biological, ecological, governance, and social objectives (Ogier et al. 2020). Such objectives can guide managers to improve the fishery performance of the fleet.

The study shows that temporal and spatial productivity analysis of fisheries can provide valuable information on the economic status of a fishery and can highlight potential problems that are not otherwise apparent. Hence, productivity analysis should be a method that is widely applied in the management of fisheries in Australia.

Conclusion

The use of productivity analysis to assess the performance of fisheries and aquaculture industries dates to the late 1980s. In Part 1 of this project, we conducted a critical review of previous studies, complemented by a bibliometric analysis, to gain an improved understanding about trends, influential work, and an identification of research gaps. We found an evolution in the focus of the literature from early attention on the direct measurement of efficiency and productivity towards asking questions regarding why and how they are at such a level or changes are occurring. The Australian literature has generally focused on characterising efficiency and productivity in various case study fisheries, using a variety of productivity methods. There is a strong theme of analysing the impact of management change in the Australian studies, reflecting the relatively sophisticated management techniques that have been implemented, with more recent investigations regarding biomass, environmental conditions, and distributional implications.

For the purpose of informing the approach to the case studies, the relevant gaps in the literature were identified as: understanding consistency of productivity indicators calculated using different methods of analysis; the link between quantity measures of efficiency and capacity and economic performance; and the impact of heterogeneity and management on outcomes.

The objective of Part 2 of this Project was to then demonstrate the use of productivity measurement and analysis as a performance indicator. Drawing upon the gaps in the literature, we structured a multi-model analysis to estimate measures of productivity in three Australian fisheries. Our three case studies explored different questions with different techniques while retaining a common backbone of calculating technical efficiency and capacity utilisation using data envelopment analysis.

For the Commonwealth Northern Prawn Fishery we contrasted results from alternative methods and showed that for this type of fishery with a relatively homogenous prices due to cooperative marketing, technical efficiency (from quantity data) is a consistent measure that is positively correlated with economic performance. Following the large buybacks in 2006/07, technical efficiency and capacity utilisation both increased, indicating a successful outcome of management intervention.

For the South Australian Spencer Gulf and West Coast Prawn Fisheries we showed that in this input-managed fishery, technical efficiency (from quantity data) is not well-correlated with economic performance as the quantity measures exhibit less variance than the value measures. Management of this fishery has adapted over time but has retained consistent objectives and overall methods hence no policy evaluation was considered.

For the Queensland Spanner Crab Fishery we took advantage of the comprehensive quantity data to investigate temporal and spatial aspects of the fleet's economic productivity. We found limited differences across time and fishing regions. The low efficiency scores indicate room for improved technical efficiency and capacity utilisation. While the management changes implemented since 1999 have led to a categorisation of the fishery as sustainable, improvements in the economic performance of the fleet are yet to materialise.

The case studies focused on DEA. DEA has particular advantages in a multispecies context over the available parametric approaches in that it does not need to impose a pre-specified functional form of the production function, enabling different production processes (including fisher behaviour) to be captured in the analysis. The estimates of efficiency derived from DEA, however, are potentially influenced by random error. Bootstrapping approaches have been developed to compensate for this to some extent (Simar and Wilson 1998, Walden 2006), but were not applied in this study. In terms of acting as a proxy indicator of economic performance, such 'random errors' reflect unexpectedly high or low catches given input use, and these will also directly influence economic performance. Hence, ignoring these random errors is, in this case, is a potential strength of DEA over the stochastic approaches that aim to remove them. DEA has also been identified as the preferred approach for the estimation of capacity utilisation in fisheries (Pascoe et al. 2003).

DEA can work with multiple species directly, while stochastic production frontier analysis requires a single (composite) output. As noted in the Northern Prawn Fishery case study, the choice of method for aggregating output can affect the measures of technical efficiency. Flexible functional forms (e.g., translog production functions) can be used in SFA, although these require the imposition of restrictions on the production process to maintain theoretical consistency.

Distance functions, as applied in the Northern Prawn Fishery case study, have the advantage that they can deal with multiple outputs directly, but their estimation requires an assumption of a common production process. Imposing theoretical consistency restrictions on the estimation of the production frontier is complex. Ex-post tests of the model in the NPF case study found that these conditions were satisfied, but this is not always the case.

The case studies also pooled the data over time, so that efficiency and capacity utilisation is estimated relative to the best observed outcomes over the complete time series. This results in the effects of stock changes being captured in the technical efficiency scores, along with other factors (e.g., management changes) that may influence fisheries. As changes in stock abundance affects economic performance, the resultant index of technical efficiency over time still represents a valid index of fishery economic performance.

Excluding stock abundance is less problematic for DEA, but may be more problematic in the case of the parametric approaches, as the statistical methods are biased by the omission of relevant variables (i.e., stock), resulting in a potentially distorted efficiency index. Incorporating a composite stock variable in a parametric model of a multispecies fishery adds additional complications, particularly if targeting behaviour of individual fishers varies.

The study has focused on the relationship between productivity measures and economic performance. We found a strong correlation between these productivity measures in the Northern Prawn Fishery, but less so for the Spencer Gulf and West Coast Prawn Fisheries. Unlike the Northern Prawn Fishery where prices received were relatively homogenous, fishers in Spencer Gulf and West Coast undertake individual marketing and sales. This results in different average prices, and hence differences in economic performance not directly related to harvesting productivity. Given that marketing and sales activities are beyond the control of managers, the productivity measures may still reflect changes in the component of economic performance that relate to management effectiveness, even if it diverges from the final, post-harvest, economic performance.

As noted in the literature review, most studies elsewhere (including several in Australia) have used the methods to estimate the impact of management changes or skipper specific factors (e.g., education or training, experience etc.) on efficiency. For these uses, SFA and distance functions are more appropriate, as efficiency can be measured directly as a function of these factors. Inclusion of a stock index directly into the production function is also necessary so that the effects of changes in stock abundance on output can be captured directly and not obfuscate the impact of the variables of interest.

Given this, we suggest that:

- DEA is used as the main method for assessing changes in economic performance over time, considering both technical efficiency and capacity utilisation, and excluding a stock measure; and
- SFA (or distance functions) are used to assess the impact of management changes or other specific factors on efficiency, with some index of stock included in the model.

The study also considered other productivity measures that are potentially of value to fisheries managers. In particular, scale efficiency – derived relatively simply using DEA – can provide information on the likely direction of adjustment in the fishery: are boats too big or too small? The proportion of boats in the fleet that are not operating at the 'optimal' (from a purely technical perspective) level also provide useful information.

Capacity utilisation also provides a measure of the extent of excess capacity in the fishery (Dupont et al. 2002). This is a short run measure only based on existing stock conditions, but considerable excess capacity is an indicator that autonomous adjustment is not taking place, and other approaches may be required to reduce fleet capacity to improve economic performance. These measures can also be directly used in a modelling context to estimate an 'optimal' fleet size given current or varied conditions. For example, (Pascoe et al. 2013) estimated the 'optimal' fleet size given different quota levels for the Torres Strait Rock Lobster fishery. In fisheries where deriving bioeconomic models are not feasible, the use of these methods provides a theoretically reliable estimate of the optimal fleet size. With limited economic data, the approach can also be used to estimate potential increases in profitability through fleet adjustment (Tingley and Pascoe 2005).

This study has demonstrated the variety of questions that can be addressed using productivity analysis, and that quantity-based measures of efficiency provide useful measures of aggregate economic performance in some scenarios. We have also shown that heterogeneity in economic outcomes at the individual level can arise even when inputs and outputs are homogenous, indicating that carefully defining the purpose of undertaking productivity analysis is important.

Implications

This study has shown that productivity analysis is a maturing field of research. There have been significant developments in methodology to allow for the challenging nature of fisheries with multiple outputs, random variation in production processes, and external factors. These methods allow robust analysis of aggregate performance of fisheries over time. There are, however, significant gaps remaining regarding the impact of dispersion, heterogeneity, inequality and institutions, and understanding the behavioural response of fishers as individuals.

The case studies have shown that use of quantity-based productivity analysis provide useful measures of economic performance in fisheries at the aggregate level when appropriate panel data are available. These quantity-based measures are more related to short-run measures of profits (such as gross margins, ignoring fixed costs) than to long-run measures at the vessel level. The two key measures considered – technical efficiency and capacity utilisation – were positively correlated with the key economic performance measures in both fisheries where detailed economic data were available. The strength of this correlation differed, however, suggesting that further case studies may be required to establish criteria for assessing the degree to which productivity measures can be considered a reliable indicator for changes in economic performance.

Fisheries management that uses both input and output quantity methods means that the levers available to fishers to improve their individual economic outcomes are necessarily via input and output price mechanisms. Changes by single fishers in large fisheries are less likely to impact upon aggregate performance but understanding how increasing divergence in smaller fisheries may be important for management practices.

The impact of management change, and the evaluation thereof, will be influenced by the objectives and methods of change. As highlighted in the Commonwealth Northern Prawn Fishery Case Study, the buybacks significantly altered the total inputs in the fishery, which lead to clear improvements in both quantity and value-based measures of performance. In the Queensland Spanner Crab Fishery Case Study, the management changes as considered in the analysis appear to have not affected productivity measures across time and fishing regions. Yet, it is likely that other regulatory restrictions and exogenous factors could have affected the economic productivity of the fishery. Hence, a more comprehensive set of variables and the continuous collection of data for these variables would offer the opportunity for advanced economic performance analysis of Australian fisheries and subsequently provide the best possible information as a basis for decision making.

Biomass data is a persistent challenge in these fisheries. The multi-species, and highly variable, nature of the NPF makes incorporating relevant stock measures extremely difficult. In addition, for all three fisheries, biomass is estimated in part or in whole using commercial catch and effort data, which requires care in applying it as an independent measure to explain efficiency. Similarly, environmental data is difficult to apply to a fishery such as the NPF with a split season. Examples in Table 1 illustrate that for fisheries with particular environmental conditions or changes of interest or concern, incorporating appropriate measures into a second-stage analysis is possible.

Even without detailed information on biomass and environmental changes, the effects of these changes on the productivity of the fishers could be observed. Similarly, effects of changes in economic conditions (price and input costs) could be detected through changes in capacity utilisation, provided vessels were not all fully utilized. The measures therefore can provide an indication of the direction and drivers of changes in economic performance, even though the degree of change may still be uncertain. The measures will therefore not replace the need for detailed economic surveys where they are routinely undertaken, but can provide timely information (and potentially real-time information) in terms of direction of economic performance in the interim. In fisheries where economic surveys are not routinely undertaken, the measures provide at least an indication of changes in economic performance in the fishery.

Each study had different data available: the large, panel nature of the Commonwealth study allowed for additional methods to be implemented with individual fixed effects proving to be important inclusions in determining the correlation between quantity and value metrics. The South Australian study was limited in its panel structure but being able to delve into the economic components allowed us to investigate the importance of considering variance as well as means. The Queensland study used a previously unknown trove of quantity data, access to which allowed a rich spatial analysis in what had been initially thought to be a data-poor fishery. As such, we note the need for a more nuanced interpretation of data-rich and data-poor and give the classic economist statement of 'it depends'. That is, appropriate data collection needs to correspond to the question and consider: the objectives of the fishery; the management scenario; potential future questions; and acknowledge that retention of and access to data for informed analysis is vital in effective decision-making.

Recommendations

This study has demonstrated that productivity analysis can be used to address a variety of questions in fisheries management including: evaluation of the impact of management change; and identifying potential for improving economic outcomes. It has also identified that quantity-based measures of productivity could be used as an effective indicator for fisheries under relatively stable management, biomass and market conditions. In addition, we have illustrated the type of analysis that can be undertaken using quantity data that has been collected within Australian fisheries and what can be done when additional economic data is available. Given this, managers and industry may wish to consider:

- Greater use of productivity analysis to evaluate impact of management change and identify fisheries for which productivity is low;
- Implementing ongoing productivity analysis as a monitoring tool in fisheries with long panels of data with associated management targets; and
- Using existing data, such as from logbooks or existing economic surveys, as a starting point and complementing this with additional economic data as it becomes available.

Further Development

This study has highlighted how productivity analysis can use existing data for monitoring, identification of potential improvement, and evaluation of change at the aggregate level. Future work to embed the use of productivity analysis as a monitoring tool in the appropriate fisheries is a sensible next step.

Only one of the fishery case studies had a detailed time series of both economic and catch-effort data where a direct comparison between the vessel productivity measure and economic performance could be made. Several other Commonwealth fisheries offer the same potential for analysis, with fisheries such as the Southern and Eastern Scalefish and Shark Fishery introducing additional challenges in terms of large numbers of species and multiple gears, while the Eastern Tuna and Billfish Fishery involves static rather than active gears. Expanding the study to include these other data-rich fisheries would provide greater insights into the limits of the approach in providing an indicator of changes in economic performance.

Gaining access to use existing confidential, vessel-level time series data was vital for each of our case studies, and many others in the literature. Similar data for other fisheries is likely to be available and under-utilised. Drawing inspiration from the Australian Bureau of Statistics 'Five Safes framework' (ABS 2022) to better enable researchers, analysts and data managers to work together to take advantage of these valuable resources would lead to opportunities to improve fisheries outcomes.

Understanding aggregate outcomes for fisheries is important for effective fisheries management. Australian fisheries do, however, tend to involve small numbers of operators. As such, changes made by one or a few fishers may lead to considerable heterogeneity in individual firm outcomes. These may then manifest in pressures on the stocks or on management decisions. Further work to understand the impact of individual heterogeneity in productivity on aggregate outcomes could allow managers additional insights.

Individual vessel data may not be available in all cases, but aggregated data may be available at different levels (e.g., monthly, annually or even spatially). The potential to apply the approaches to different levels of data was not investigated in this study, but again is an area for further consideration.

Extension and Adoption

The substantive results from the primary research undertaken for this project are largely to be disseminated through this report and journal articles that are produced from the literature review and case studies. Four papers are currently in preparation for submission to academic journals. They draw on Part 1, and each of the case studies in Part 2 of the project.

The Guidelines for Managers were released in conjunction with a Webinar “Using Productivity in Fisheries Management”, held in May 2022. The webinar was attended by approximately 50 people from across Australia and New Zealand. A recording of the webinar and the Guidelines are available on the Project website: https://www.frdc.com.au/project/2019-026

Short overview videos are in preparation: one summarizing the whole project; and one for each of the case studies. These will be available on the Project website: https://www.frdc.com.au/project/2019-026. We plan to release the videos via FRDCs ‘Fish News’ monthly email.

Planned presentations at the primary international fisheries economics conference (IIFET) were thwarted due to Covid. The following two presentations from this project were given at the World Fisheries Congress 2020, with the latter submitted to be presented at the New Zealand Agricultural and Resource Economics Society Conference.

- Relationship between efficiency, capacity utilization and economic performance of vessels and fleets – presented by Sean Pascoe
- Measuring, interpreting and monitoring economic productivity in an input-controlled fishery: the case of South Australian prawns – presented by Stephanie McWhinnie

Project Materials Developed

Journal Articles

- "Trends in efficiency, capacity utilization and productivity analysis in fisheries and aquaculture: A review" manuscript in preparation
- "Relationship between efficiency, capacity utilization and economic performance of vessels and fleets in Australia's Northern Prawn Fishery" manuscript in preparation
- "Measuring, interpreting and monitoring economic productivity in an input-controlled fishery: the case of South Australian prawns" manuscript in preparation
- "Spatial and temporal fishery management assessment using DEA: Case study of spanner crabs in Australia" manuscript in preparation

Guidelines for Managers

- "Measuring, interpreting and monitoring economic productivity in Australian fisheries" Available on the project website https://www.frdc.com.au/project/2019-026

Video Content

- "Using Productivity in Fisheries Management" webinar recording
- "Measuring, interpreting and monitoring economic productivity in Australian fisheries" project overview
- "Measuring, interpreting and monitoring economic productivity in the Commonwealth Northern Prawn Fishery" case study summary
- "Measuring, interpreting and monitoring economic productivity in South Australia's Spencer Gulf and West Coast Prawn Fisheries" case study summary
- "Measuring, interpreting and monitoring economic productivity in Queensland's Spanner Crab Fishery" case study summary in preparation
  To be available on the project website https://www.frdc.com.au/project/2019-026

Appendices

Appendix A. Researchers Involved with the Project

The core research team consisted of

- Stephanie McWhinnie, University of Adelaide
- Sean Pascoe, CSIRO Oceans and Atmosphere
- Peggy Schrobback, CSIRO Agriculture and Food
- Eriko Hoshino, CSIRO Oceans and Atmosphere
- Robert Curtotti, ABARES

Input into the project was also provided by

- Anders Magnusson, BDO EconSearch
- John Kandulu, BDO EconSearch
- Steve Shanks, Department of Primary Industries and Regions South Australia
- Sian Breen, Queensland Department of Agriculture and Fisheries
- Nancy Trieu, Queensland Department of Agriculture and Fisheries
- Bryan McDonald, Northern Territory Department of Industry, Tourism and Trade

Appendix B. Compendium of Examples of Economic Productivity Analysis in Fisheries

Table 17. Summary of Australian efficiency and productivity publications

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Kompas et al. (2004) *Appl. Ec.* DOI URL	Estimate efficiency effects of input controls	Northern prawn fishery	1990-2000	logbook daily data aggregated to annual on catch + vessel chars. 37 vessels for 228 observations	Input controls	SFA then estimate TE depending on engine and vessel size (restricted)	Substitution from regulated to unregulated inputs, TE has declined
Kompas and Che (2005) *J. Prod. An.* DOI URL	Estimate efficiency gains from ITQs	South-east trawl	1997-2000	logbook daily data aggregated to annual on catch + vessel chars. 47 vessels for 131 observations	ITQ	SFA to estimate TE and components of costs	TE high overall (90%) and rises when more quota is traded
(Greenville et al. 2006) *Mar. Res. Ec.* DOI	Estimate impact of input controls on TE	NSW prawn trawl	1997-2003	aggregated to annual 61 vessels catch, effort and boat characteristics	Input controls	SFA to estimate relationship between TE and controlled and uncontrolled inputs	Input controls lower TE but without long-run effects on productivity
Fox et al. (2006) *AJARE* DOI URL	Assess performance after licence buyback and quota trading	South-east trawl	1997-2000	logbook aggregated to annual for 120 observations (47 vessels, unbalanced panel)	ITQ with licence buyback	Index number decomposition - then comparison of means - accounting for biomass	Large range in relative profits and productivities. Output prices and productivity higher since buyback. Buyback helpful

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Szakiel et al. (2006) *AARES conf.* URL	Review a range of different approaches to measure capacity and capacity utilisation	-	-	-	-	Methods review	Suggests that quantitative measures are difficult (require a computer) but qualitative indicators are useful (and don't require a computer). Qualitative indicator may be non-binding TAC or use of input controls
Pascoe et al. (2010) *Eur. Rev. Ag. Ec.* DOI URL	Estimate ability to target fishing activity in a multispecies fishery	Northern prawn fishery	1995-2007	logbook daily data aggregated to weekly on catch + vessel chars. 130 - 51 active boats	From TAC and input controls to ITQ in 2012	Estimate TL multi-output distance function with Bayesian estimation to determine ability to substitute outputs and hence whether separately set ITQs are ok	Multi-output distance function good b/c need quantity data. Jointness in NPF means a single quota probably ok
Pascoe et al. (2011) *AJARE* DOI URL	Estimate profit maximising vessel size and output levels under ITQs	Northern prawn fishery	1994/5 2005/6	logbook daily data aggregated to annual on catch + vessel chars. 265 total observations	From TAC and input controls to ITQ in 2012	Estimate restricted TL profit function normalised by one output price to determine elasticities of outputs and inputs	Fewer, larger vessels likely to remain under ITQs. Power rather than fishing days
Perks et al. (2011) *AARES conf.* URL	Assess TFP based on financial and catch data	Commonwealth Trawl Sector of the Southern and Eastern Scalefish and Shark Fishery	1996/7 to 2008/9	ABARES survey data	ITQs from initial implementation	Fisher index method	Both outputs and input use declined over the period of the data. TFP initially declined, but then increased towards the end of the period (after the fleet had been reduced through the fishery buyback)

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Vieira (2011) *NAAFE conf.*	Drivers of profit change	Commonwealth Trawl Sector of the Southern and Eastern Scalefish and Shark Fishery	1998/9 and 2008/9	ABARES survey data	ITQs	Profit decomposition (index number approach)	Notes issues with ignoring variable inputs in the profit decomposition approach – only fixed inputs are included
Vieira (2011) *AARES conf.* URL	Drivers of profit change	Trawl and gillnet sectors of the Southern and Eastern Scalefish and Shark Fishery	1998/9 and 2008/9	ABARES survey data	ITQs	Profit decomposition (index number approach)	Extension of above study
O'Donnell (2012) *Prod. Msmt Workshop* URL	Estimate productivity and efficiency with small, quantity data in regulated industry	Northern prawn fishery	1974-2010	logbook daily data aggregated to annual on catch + vessel chars. 37 annual x 26 years	TAC and input controls	Bayesian methods of SFA to decompose Fare-Primont indexes of TFP. FP b/c decomposable and quantity data. Bayesian b/c resolves endogeneity in multiple input and output models and small-sample properties are good	Productivity rose due to production environment, technical efficiency, but scale inefficiency rose due to downsizing in an industry that has increasing returns to scale
New (2012) *AARES conf.* URL	Estimate effects of changes in management on the fishery efficiency	Eastern Tuna and Billfish Fishery	2001/2 to 2010/1	Logbook data (annual) vessel level plus vessel characteristics	Input controls to ITQs	Stochastic production frontier. Composite output measure derived using fisher index method	Buyback had little impact on technical efficiency of the fleet. No evidence of effort creep due to input controls

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Skirtun and Vieira (2012) *ABARES tech. report* URL	Estimate drivers of profitability in Commonwealth fisheries	Commonwealth Trawl (CTS), Shark gillnet sector, northern prawn (NPF), Torres St prawn (TSPF)	1998-2009	ABARES vessel-level inputs (labour, fuel, repairs, capital) and outputs (as appropriate), biomass if available	Buybacks and move to incentive-based management	Index number decomposition - then comparison of means - accounting for biomass where possible	CTS: profitability rose from 2004, output prices up, structural change from fleet reduction. SGS: profit fell 1999-2005 but recovered after, productivity improvement, vessel buybacks, MEY focus. NPF: Tiger prawn profit fell to 2004, some recovery but still not up to 2001, falling prices. Banana prawn profit fell to 2004 b/c output prices, higher profit since b/c productivity, vessel buybacks. TSPF: profitability fell throughout, productivity main driver, higher prices mitigated
Skirtun (2013) *AARES conf.* URL	Drivers of profitability in two key Commonwealth fisheries	northern prawn (NPF), Torres St prawn (TSPF)	1998/9 to 2009/10.	ABARES survey data	Input controls with buyback	Profit decomposition (extension of above study)	Output price and productivity change main drivers of profitability in NPF; productivity main driver in TSPF
Pascoe et al. (2012) *J. Ag. Ec.* DOI URL	Estimate average efficiency of vessels that remained after buyback	Northern prawn fishery	1995-2007	logbook daily data aggregated to weekly on catch + vessel chars. 130 - 51 active boats. 24259 observations from 164 vessels	From TAC and input controls to ITQ in 2012.	Estimate TL multi-output production frontier explicitly including vessel numbers and jointly estimated with inefficiency model	Average efficiency of remaining vessels higher after buybacks, and least efficient vessels exited. Search externalities were positive but smaller than negative crowding externalities. Buyback benefits generally short-lived, move to ITQs will hopefully lessen the problem here

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Pascoe et al. (2013) *Can. J. Ec.* DOI URL	Estimate marginal value product of two fleet segments to determine if total catch should be reallocated	Torres Strait tropical rock lobster	1994-2010	logbook data per tender day, 48 vessels for non-Islander, 333 Islander	TAC split between Islander and non-Islander fleets, goal to increase Islander share	Estimate TL production function of each sector	Islander fleet could take goal of 70% catch with existing fleet and benefits are higher but unlikely to be by enough that purchasing of quota from non-Islander will occur independent of intervention. Individual quota unlikely best management for Islander fleet
Stephan and Vieira (2013) *ABARES tech. report* URL and Stephan (2013) *AARES conf.* URL	Measure TFP over time for key commonwealth fisheries	Eastern Tuna and Billfish (ETBF), Commonwealth Trawl (CTS), Gillnet, Hook and Trap Sector (GHTS) of Southern and Eastern Scalefish and Shark Fishery (SESSF), Northern Prawn (NPF), Torres Strait Prawn (TSPF)	1990 or 1994 - 2010 or 2011	ABARES vessel-level inputs (labour, fuel, repairs, capital) and outputs (as appropriate), biomass if available	Buybacks and move to incentive-based management	Fisher Index of inputs and outputs at vessel level, then aggregated to fishery-level TFP, adjusted for biomass where/when possible	Productivity generally increased, particularly since buyback completed. ETBF 6.7% overall, mostly since 2003 due to fleet reduction b/c market conditions and buyback. Otter trawlers in CTS 10% overall, fastest since 2004 with lower stocks and lower vessels. GHTS 1-2%, declined before 2003 then rose as vessel numbers fell, note area closures due to seals. NPF 7%, mostly since 2004, Tiger prawn stock adjusted only 3% mostly since 2004 with buybacks and MEY targets, Banana prawn 10% but stock not fully available but likely high. TSPF 4.8%, mostly since 2000, vessels declined, biomass likely rose

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Pascoe et al. (2013) *Eur. J. Op. Res.* DOI URL	Consider whether technical and scale efficiency and capacity utilisation measures are good predictors of which vessels remain after switch to ITQs. See how DEA measures can be incorporated into Management Strategy Evaluation	Torres Strait tropical rock lobster	2007-2009	logbook data, annual. 25 vessels down to 11. 47 total observations	buybacks 2008, moving to ITQ	Estimate DEA (output) then use TE, SE, CU to predict probability of exit using a logit regression	Fleet does not decrease linearly with reduced quota. CU major predictor in who will exit
Schrobback et al. (2015) *PLOS ONE* DOI URL	Estimate efficiency and capacity in shore-adjacent aquaculture	Moreton Bay oyster aquaculture	1997-2012	Output and input volume and value 39 farms from govt. 113 observations total. Survey data for demographics	Licences for exclusive lease areas within Marine Park	DEA (multi-output revenue) for TE, CU followed by Tobit and OLS estimation depending on farmer characteristics and environmental conditions	High CU, low efficiency. Improved water quality and training likely to improve most
Productivity Commission (2016) *Tech. report* URL	Identify opportunities to increase productivity and cut unnecessary and costly regulation in fisheries mgmt	--	--	--	--	Report based on review of literature, submissions, some data	Input controls inhibit innovation and cost-effectiveness; recreational and Indigenous fishing activity poorly understood; not-consistent management across jurisdictions increases cost and increases risk to sustainability. Consistent regulation, use ITQs rather than input etc controls, consider econ and social, include rec and Indigenous, streamline environmental rules

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Green (2016) *AARES Conf.* URL	Estimate level and distribution of inefficiency	Trawl Sector of the Southern and Eastern Scalefish and Shark Fishery	2003 - 2013	ABARES survey data - vessel level data	ITQs	Stochastic production frontier; Fisher index for the quantity (output) measure	Wide variability in efficiency scores in the fishery. Least efficient vessels left during the restructure
Pascoe et al. (2017) *Fish. Res.* DOI URL	Estimate effect of reducing investment disincentives	Moreton Bay prawn trawl	2005-2010	logbook data, daily aggregated to monthly	Input controls	Estimate SPF (output) for relationship between inputs and outputs; then estimate marginal profitability; then consider removal of policy by calculating 'hull unit' elasticity	Removing the two-for-one replacement policy unlikely to increase effort b/c of vessel unitisation limits
Rust et al. (2017) *Mar. Pol.* DOI URL	Estimate dynamic behaviour of excess capacity under quota management	Tasmanian rock lobster	2000-2013	logbook data, daily aggregated to monthly, 3120 observations	ITQ since 1998, TAC non-binding 2008-2010	DEA (output) of capacity, capacity utilisation, overcapacity	Limited ability of ITQ to alleviate excess capacity - but can't say if economically inefficient or kept capacity in case of higher stocks in future
(Pascoe et al. 2018) *AJARE* DOI URL	Estimate efficiency within a fleet to determine when vessels leave fishery in season and effect on MEY triggers	Northern prawn fishery	2010-2015	logbook daily data aggregated to weekly on catch + vessel chars. 62 vessels	MEY trigger based on average costs introduced in 2013	Estimate SPF to determine if TE changes over the season; and estimate if variable costs constant over season without having cost data	MEY target and trigger seems pragmatic. Higher costs towards end of season likely, indicating trigger targets too low
Pascoe et al. (2019) *Mar. Pol.* DOI URL	Estimate drivers of profitability	NSW rock lobster	2000/1 to 2018/9	Quota trading and market (price) data	ITQs	Profit decomposition	Although stocks had improved over time, price was the main driver of profitability in the fishery

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Otumawu-Apreku and McWhinnie (2020) *Mar. Pol.* DOI URL	Estimate profit efficiency under different management regimes	SA lobster	1997-2008	272 vessel-level observations from survey	From TAC to IQs (north) and IQs (south)	Nerlovian and directional distance function methods (DEA) of profit efficiency decomposed into technical and allocative	Unlike profit levels comparison, profit efficiency is similar in north and south
Otumawu-Apreku and McWhinnie (2021) *Mar. Pol.* DOI URL	Develop theory for including fixed inputs in efficiency analysis and empirically examine in SA lobster case	SA lobster	1997-2008	272 vessel-level observations from survey	From TAC to IQs (north) and IQs (south)	Theoretical model with short v. long run capital. Then truncated bootstrapped regression of DEA efficiency scores on exogenous characteristics	Profits higher if vessel is operating closer to optimal size. Stocks harmed if sub-optimality costs are low enough. Prices good for profit in short-run but can be negative in long-run through biomass effect

Table 18. Summary of international efficiency and productivity publications referenced in Table 1

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Jin et al. (2002) *J. Env. Ec. Mgmt* DOI URL	Calculate aggregate TFP for fishery as a whole including stock abundance	New England, USA, groundfish	1964-1993	Trip-level output and value aggregated to annual. Days at sea and tonnage class. Costs estimated	Output and effort controls	Estimate production function using Tornqvist indices a la Squires 1992	TFP increased 4.4% pa over time. Higher until 1982, lower since due to output and effort controls
Vestergaard et al. (2002) *Tech. report* URL	Use a consistent DEA approach to analyse capacity in EU fisheries at firm and industry level with multi-inputs and multi-outputs	Various EU (UK, Netherlands, Belgium, Germany, France, Denmark)	1990s	Various. Trip-level catch and effort (quantities) aggregated to monthly or annual and by fishery/industry/gear type	Various.	DEA with second stage regressions. Clearly specifies a consistent methodology and outlines both DEA and second-stage methods	UK 80% CU and stock abundance matters. France CU depends on flexibility to operate with different gears or in different fisheries. Belgian beam trawl CU 88%. German beam trawl CU 34% and stock abundance matters. Dutch beam trawl (plaice and sole) CU 84% north and south different and vessel size matters. Dutch beam trawl (shrimp) CU 46%, stocks matter. Denmark input reallocation would improve performance, netters decreased while trawlers increased efficiency
Felthoven (2002) *MRE* DOI URL	How did policy change affect TE/CU using general indicators of earnings	Alaskan Pollock catcher-processors	1994-2000	Annual data for 30 vessels = 180 observations	Reduction of TAC, buybacks, coop formation to mimic ITQ benefits	DEA and SFA (output) to calculate TE, CU, capacity	Capacity fell but TE and CU rose

Reference	Question	Fishery	Period	Data	Management	Method	Conclusion
Fox et al. (2003) *J. Env. Ec. Mgmt* DOI URL	Develop new index number decomposition and estimate effects on profitability of ITQs	British Columbia Halibut	1988 - 1994	105 firm-level observations on input and output quantity and value	Licence to ITQs	Index number decomposition - then comparison of means - accounting for biomass	ITQs increased profitability b/c output prices rose, and larger vessels better
Sandberg (2006) *Appl. Ec.* DOI URL	How do variable costs depend on output and stock	Herring and cod, Norway	1990-2000	Annual cost and catch. Vessel level. Unbalanced. 1229 vessels, 37229 total observations	TAC and IVQ	Estimate cost function (Cobb-Douglas) dependent on output and stock	Variable costs decrease with output and decrease with stock in the demersal fishery
Asche et al. (2008) *Mar. Pol.* DOI URL	Do IVQs increase rents and decrease capacity	Multispecies with cod focus, Denmark, Iceland, Norway, Sweden, UK	1997-99 (N), 1995-00 (I&D), 2001 (S&UK)	Firm-level observations on input and output quantity and value	IVQ (N&S&D) ITQ (I&UK)	Cost function estimation (TL or Leontief) to get optimal vessels and profits then calculate how far from this the fisheries are	Fleet reduction of more than half needed to get efficient fleet size. Transferability important. Buybacks unlikely to work
Färe et al. (2011) *Eastern Econ. J.* DOI URL	How to best measure capacity/efficiency when some outputs are undesirable	Otter trawl for whitefish, Georges Bank USA and Canada	2003-2005	299 trips from 127 vessels	DDF & hyper-bolic efficiency measures with/without undesirable outputs & inputs	Difficult to reduce undesirable outputs without reducing desirable outputs	Excluding undesirable outputs misspecifies capacity and efficiency
Thunberg et al. (2015) *Mar. Pol.* DOI URL	Estimate productivity change for 20 catch-share fisheries	Various USA	Varous 1987-2010	Regional level quantities and prices	From TAC etc to catch shares (various dates from 1990)	Lowe Multifactor Productivity Index with and without biomass	Productivity rose for most in first 3 years after catch shares, and maintained or grew further after

Reference	**Question**	**Fishery**	**Period**	**Data**	**Management**	**Method**	**Conclusion**
Chen et al. (2016) *Nat. Hazards* DOI URL	Does ambient water quality affect TE?	Lobster Connecticut Long Island Sound USA	1998-2007	Monthly, industry-level data	licences	DEA of TE then bootstrapped censored quantile regression for environmental conditions	When environment good, TE low; when environment bad, TE high. Different environmental measures impact at different quantiles
Scheld and Walden (2018) *MRE* DOI URL	Does fishing selectivity change after rights-based management introduced	New England, USA, groundfish	2007-2014	Tow-level catch data: 40692 tows by 408 vessels across 8 years	To rights based management 2010	Estimate directional distance functions under strong v. weak disposability, followed by quantile regression controlling for spatial, temporal & individual factors	Selectivity increased after rights based but still imperfect selectivity
Ekerhovd and Gordon (2020) *Env. & Res. Econ* DOI URL	How has profitability, capacity and productivity changed over time with ITQs	Norwegian purse seine	1994-2013	Vessel obs. From detailed annual 372 - 1243 observations	Licences in 70s, IVQs for capelin 1978, mackerel and herring IVQ late 80s	Index number decomposition to identify effect of prices, output and regulatory change	Price the main drivers of higher revenues, capital investment not associated with higher harvest, caused productivity to decline in early periods

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