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Quantitative Methods for Producing Evidence to Support Sustainable King Scallop Management

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Award date:
2020

Awarding institution:
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Quantitative Methods for Producing Evidence to Support Sustainable King Scallop Management

PhD thesis

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School of Ocean Sciences

May 2020

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ACKNOWLEDGEMENTS

I would like to thank my supervisors, who I have thoroughly enjoyed learning from, working alongside and getting to know. Professor Michel Kaiser initiated the project and provided excellent support, direction and feedback throughout all aspects of the project, even after leaving Bangor University shortly in to the third year of the project. Professor Jan Hiddink moved from secondary to primary supervisor after Mike's departure and I also thank Jan for his fantastic guidance and detailed input to the PhD, especially in the analysis and write-up stages. I also thank Dr Gwladys Lambert for sharing extensive knowledge of the datasets used in this thesis and extensive knowledge of implementing stock assessments, as well as all the thorough advice and input when writing this thesis. I am also grateful for Dr Claire Szostek's help with fieldwork and general support and understanding of undertaking a PhD on the topic of scallop fisheries.

My thanks also go to both Dr Aidan Hunter and Dr Douglas Speirs for their teaching of, and help with, implementing the complex stock assessment models implemented in this thesis. I also thank the various captains and crew of the RV Prince Madog for their help and adaptability under ever-changing conditions on the multiple research surveys I had the pleasure of conducting. I thank the School of Ocean Sciences technicians Ben Powell, Peter Hughes, Aled Owen and Rob Evans for all their help preparing for research at sea. Similarly, I am grateful for all volunteers who spent their time helping count, sort and dissect scallops. In particular, I thank Claire Szostek, Ashton Budd and Christopher Brodie for their help on multiple research surveys. Additionally, I'm grateful to Anneli Lofstedt for field work help and for help dissecting many scallops. I am also fortunate to have conducted this research at the School of Ocean Sciences and within the friendly, helpful, and supportive PhD student community based in this department.

I thank my funding body Knowledge Exchange Skills Scholarships 2 (KESS 2), and my supervisor from the Welsh Fishermen's Association Jim Evans. KESS 2 is funded by the European Social Fund through the Welsh Government, and funding from commercial partners. In this case the commercial partners were the Welsh Fishermen's Association, AM Seafoods Limited, Sainsbury's Supermarkets Ltd, FalFish Limited, Young's Seafood, Coombe Fisheries Ltd, Wm Morrison Supermarkets PLC and Mark Roberts.

Finally, I thank my family and close friends for supporting me through this part of my career and wider journey.

ABSTRACT

Scallops were the third most valuable wild-caught marine animals in the United Kingdom (UK) in 2018, with a first-sale value of £69.7 million. Despite the high relative and absolute economic value of scallop fisheries in the UK, the majority are not managed based on quantitative scientific evidence from stock assessments which risks them becoming overfished and unsustainable. Scallops were also the third most valuable wild-caught marine animals in Wales, at a first-sale value of £2.4 million. Despite this Welsh scallop first-sale value being approximately 3.4 % of the value of the wider UK fishery, the fishery is still relatively economically important to Wales as the third most valuable. In addition, landings of scallops in to Wales have been decreasing since 2012 which highlights that greater scientific evidence is required to support the sustainable management of this relatively economically important natural resource. The existing management tools in Welsh waters are not linked to evidence of scallop stock sizes, or any other measure of scallop stock status. In addition to these arguments for sustainably managing the scallop populations, scallop dredging is considered to have a negative impact on the wider ecosystem and therefore it is important to gain a greater understanding of the negative effects of scallop dredging so that these may be better managed.

The aims of this study were to implement techniques to estimate two valuable pieces of evidence which could help support sustainable management of king scallops (*Pecten maximus*) in Wales. These pieces of evidence were; (1) estimates of absolute stock sizes and (2) the effect of repeatedly applying fishing effort to an area on the target species, the wider environment and fuel efficiency. Multiple historical reconstruction stock assessment models and a spatial depletion model were used to directly estimate absolute size of stocks or populations, and the catch efficiencies of multiple commercial vessels were quantified with a view towards scaling catch rates to abundance using catch efficiency in the future. The three historical reconstruction stock assessment models varied by estimated stock structure and were age-, length- and un- structured, where unstructured models are more commonly known as surplus-production or biomass dynamics models. The effects of repeatedly fishing small areas on environmental fishing efficiency and fuel efficiency were investigated through simulations and empirical data.

The estimated catch efficiencies of five commercial scallop vessels ranged from 0.13 to 0.62, which demonstrated high variability in catch efficiencies between the vessels and between estimates for the same vessel. This indicated that catch efficiencies can vary considerably between scallop dredgers and catch rates should be not be scaled to estimates of abundance using catch efficiency until greater understanding of catch efficiencies is achieved. Scallop density was found to vary considerably over small spatial scales (25 to 59 commercially sized scallops per 100 m^2) and was not linked to sediment type. This reinforces the need for fishery-independent surveys to determine fine spatial scale fluctuations in scallop densities. Catch efficiency was also shown to be important when understanding the environmental impact of scallop dredging relative to catch as areas were repeatedly fished. In particular, vessels with a catch efficiency higher than the benthic depletion rate would cause a greater environmental impact relative to their catch as small areas are continued to be fished. This insight could be used to evaluate the trade-off between quantity of catch and environmental impacts of fishing and used to determine an effort threshold for vessels of particular catch efficiencies that could be used in a rotational management strategy.

The size of a king scallop stock in Wales was estimated by three different historical reconstruction stock assessment models and collectively these models also estimated a wide range of useful rates, states and parameters for scallop fisheries and life history including annual fishing mortality rate, recruitment, selectivity, catch efficiencies, maximum

sustainable yield and more. In addition to these rates, states and parameters being directly useful for future analyses of this fishery, they would also be useful as prior distributions in stock assessments of other king scallop fisheries. Furthermore, it was shown that the unstructured model produced similar outputs (estimates of stock size and biological reference points) to the age-structured model which both agreed and disagreed with other studies.

These key pieces of evidence allowed the proposal of strategies to attempt to manage the Welsh scallop fishery sustainably. Two proposed strategies to reduce fishing mortality included imposing catch limits and by setting effort limits. These strategies could be applied to large regions of Welsh waters, relatively small areas or as limits on individual vessels. The primary recommended strategy is to use rotational management of small areas combined with effort limits assigned to vessels based on knowledge of catch efficiencies.

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ACRONYMS

AUV	Autonomous underwater vehicle
B_{MSY}	Stock biomass when the MSY is continually removed over time
CASA	Catch-At-Size-Analysis (model name)
CSA	Catch Survey Analysis or Collie-Sissenwine Analysis (two names for the same model)
DFO	Department of Fisheries and Oceans (alternatively Fisheries and Oceans Canada)
EAF	Ecosystem approach to fisheries
EBFM	Ecosystem-based fisheries management
EEZ	Exclusive Economic Zone
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
F_{MSY}	The fishing mortality rate required to catch the MSY
FSA	Simples Fisheries Stock Assessment Methods (R package)
GHG	Greenhouse gases
GPS	Global Positioning System
HMC	Hamiltonian Monte Carlo
IA	Integrated analysis
ICES	International Council for the Exploration of the Seas
IoM	Isle of Man
ITQ	Individual transferable quota
LPUE	Landings per unit effort
MCMC	Markov Chain Monte Carlo
MEY	Maximum economic yield
MLS	Minimum landing size
MMO	Marine Management Organisation
MSC	Marine Stewardship Council
MSY	Maximum sustainable yield
NAO	North Atlantic Oscillation
NEFSC	Northeast Fisheries Science Center
NMFS	National Marine Fisheries Service
NOAA	National Oceanic and Atmospheric Administration
NPFMC	North Pacific Fishery Management Council
PI	Prediction interval
PPR	Production per recruit
RBS	Relative benthic status
SAC	Special Area of Conservation
SCA	Statistical-catch-at-age
SPR	Spawning potential per recruit
SSB	Spawning stock biomass

STECF	Scientific, Technical and Economic Committee for Fisheries
SYM	Stochastic Yield Model (model name)
TAC	Total allowable catch
TSA	Time Series Analysis (model name)
TSB	Total stock biomass
UK	United Kingdom
US/USA	United States (of America)
VMS	Vessel Monitoring System
VPA	Virtual population analysis
YPR	Yield per recruit
ΔRBS-PUL	Change in relative benthic status per unit (of catch) landed

CHAPTER 1: INTRODUCTION

The aim of fisheries science is to provide scientific evidence to help management support sustainable fisheries, and draws on disciplines such as biology, conservation, management, economics, mathematics and statistics. Modern definitions of a sustainable fishery often incorporate the wider ecosystem as well as the target species (Pauly et al 2002). Such a focus involves monitoring and quantifying the impact of fishing gears on non-target species, benthic communities and the physical marine environment. In addition, sustainable fisheries management may also incorporate socio-economic factors and consider those whose livelihoods are dependent on the health of the target species and the wider ecosystem. Various modern terms for this approach to fisheries management exist, such as ecosystem-based fisheries management (EBFM) or the ecosystem approach to fisheries (EAF) (Garcia 2003). EBFM is a term usually associated with any management strategy which has a focus that considers the ecosystem as well as the target species (Link et al 2011; Lambert et al 2017). EAF differs from this as EAF is not restricted to management and may include areas of research such as human well-being and governance (Garcia 2003).

The need to manage fisheries sustainably has arisen from a high global demand for seafood, advances in technologies and an increasing global fishing industry (Tidwell and Allan 2001; FAO 2014). A combination of these factors has resulted in fishing occurring on large scales, and consequently the percentage of overfished global fish (fin- or shell-fish) stocks has increased from 10% in 1974 to 33.1% in 2015 (FAO 2018) despite global fish catches now declining (Golden et al 2016). In addition to jeopardising fish yields, overfishing can negatively alter habitats and communities (Hauge et al 2009). Although not all fish stocks are overfished (66.9% of global fish stocks in 2015 were deemed biologically sustainable) (FAO 2018), it is important to manage fisheries to avoid further stocks becoming overfished and to ensure that healthy marine ecosystems can be maintained and used in the future (Pauly et al 2002).

Effective management of fisheries consists of, but is not limited to, suitable monitoring, appropriate stock assessment, effective use and enforcement of management tools and consideration of economic and environmental impacts of fishing (Tindall et al 2016). A wide range of management tools have been implemented in global fisheries including spatial, temporal, gear, vessel, catch and access regulations (Cochrane 2002; Orensanz et al 2016). These regulations are particularly important as they allow for a control of fishing effort and can provide protection to the stock and the wider ecosystem (Cochrane 2002; Cinner et al 2007). It is important that management regulations are supported by evidence of the status of the target species and the wider ecosystem, as the best decisions rely on both knowledge of the current status of the fishery and the future impacts of management decisions (Cochrane 2002).

Gathering evidence for fisheries management involves, as a minimum, monitoring of the fishery. Monitoring of a fishery involves directly obtaining information from the fishery, such as catch rates or fisheries-independent survey indices. Stock assessment is a commonly used name for analysis of fisheries data which involves the use of mathematical and statistical calculations to quantify the status of a local aggregation of a target species, or stock (Hilborn and Walters 1992). A key piece of evidence often produced from a stock assessment is a relative or absolute measure of the size of the target species stock (Hilborn and Walters 1992). Understanding the size of the target species stock is particularly important to avoid overfishing. However, it is also important to understand the impacts of fishing in a broader context than the target species. Therefore, quantifying the impact that fishing has on both the target stock and wider ecosystem are also key pieces of evidence for sustainably managing a fishery.

1.1 Scallops and their fisheries

Scallop (Pectinidae) fisheries are of considerable local and global importance, with large increases in landings occurring throughout the last 20 years (FAO 2014; Stewart and Howarth 2016). Scallop fisheries in the UK consist of king scallop (*Pecten maximus*) and queen scallop (*Aequipecten opercularis*) and landings of king scallop have increased over the previous 50 years (2,500 tonnes in 1968 and 32,600 tonnes in 2017) (Beukers-Stewart and Beukers-Stewart 2009; MMO 2018). Other scallop species are important in other areas and make up other major fisheries around the world in temperate seas (Table 1.1).

Table 1.1: The value and importance of selected major scallop fisheries.

Fishery	Landings Value	Landings (thousand tonnes)	Fishery Rank (all fisheries)	Reference
US sea scallop (*Placopecten magellanicus*) and weathervane scallop (*Patinopecten caurinus*)	$511.9 million (2017)	23.45 (meat weights)	Fifth most valuable in US (2017)	NMFS 2018
UK king scallop and queen scallop	£69.7 million (2018)	28.8 (live weight, including shell)	Third most valuable in UK (2018)	MMO 2019
Canadian sea scallop	Can$175.7 million (2017)	55.94 (live weight)	Fourth most valuable in Canada (2017)	DFO 2019

The increase in landings means there is greater effort being expended to harvest scallops. It is therefore important that scallop fisheries are managed effectively to avoid overfishing of the target stocks and minimise impacts on the wider ecosystem caused by expending additional effort. Therefore, the monitoring methods and analysis techniques of scallop stocks are of considerable importance so that evidence is available to underpin management (Murray et al 2013; Hartill and Williams 2014). In addition, it is also extremely important to understand how the biology and fishing methods affects the analyses and management of scallops.

King scallops are northeast Atlantic bivalve molluscs (Figure 1.1) and they are hermaphroditic, meaning an individual will produce both sperm and eggs (Cragg 2016). They employ a broadcast spawning technique where fertilisation of sperm and eggs occurs in the water column (Cragg 2016). However, the quantification of king scallop recruitment (new individuals born to a population) is generally poorly understood and is likely to be dependent on environmental factors (Beukers-Stewart and Beukers-Stewart 2009; NPFMC 2014; ICES 2016). The species conducts the majority of growth and recruitment between March and October when there is warmer sea temperatures and greater food availability (Beukers-Stewart and Beukers-Stewart 2009; Chauvaud et al 2012). Once recruited and settled, king scallops live partially buried in the seabed and are semi-sedentary (Howell and Fraser 1984; Brand 2016). They are able to swim as an escape response, yet the species have been shown to move less than 30 m over a period of 18 months (Howell and Fraser 1984). This means that from year to year the location of scallop populations should not vary considerably.

In the UK, king scallops are typically fished using spring-loaded Newhaven dredges (Figure 1.1). Dredges are typically towed on bars of three to twelve (gangs) from each side of a vessel (Lart 2003). Each dredge consists of a spring-loaded toothed bar designed to allow for give when the gear encounters boulders (**Error! Reference source not found.**). The toothed bar dislodges scallops such that they are caught in a chainmail bag (Boulcott et al 2014). The gear is known to impact both the seabed communities and physical seabed, and therefore the environmental impacts of scallop dredging is of importance to management (Collie et al 2000; Kaiser et al 2006; Stewart and Howarth 2016).

Figure 1.1: Images of a scallop and a Newhaven dredge. Top left is the underside of a king scallop. Bottom left is the topside of a king scallop. Right is a Newhaven dredge bag full of king scallops. The dredge is attached to a tow bar which supports other dredges. Source: Adam Delargy (scallops) and Claire Szostek (dredges).

Figure 1.2: A diagram of a Newhaven spring-loaded dredge. Source: Seafish www.seafish.org

There are a number areas in the waters surrounding the UK where king scallops are fished (Figure 1.5). The areas with the highest landings are found in the eastern English Channel and other areas with sizeable annual landings are found in the western English Channel, Cardigan Bay, the north Irish Sea and north-east Scotland (STECF 2018). These areas are important for the UK scallop fleet, and vessels from the Republic of Ireland and France also fish for king scallops in some of these areas. The UK scallop dredge fleet consisted of 285 vessels in 2018, of which 204 were less than 15 m long and the remaining 81 were 15 m or more in length (Seafish 2019). The over 15 m vessels are highly specialised, with king scallops consisting of 92% of their landings in 2018 (Seafish 2019). The vessels less than 15 m land are less specialised, but king scallops still made up the majority of their landings (67%) (Seafish 2019). More detailed information on the size structure and distribution of the UK scallop dredge fleet around the UK can be obtained from data from 2017 (Table 1.2).

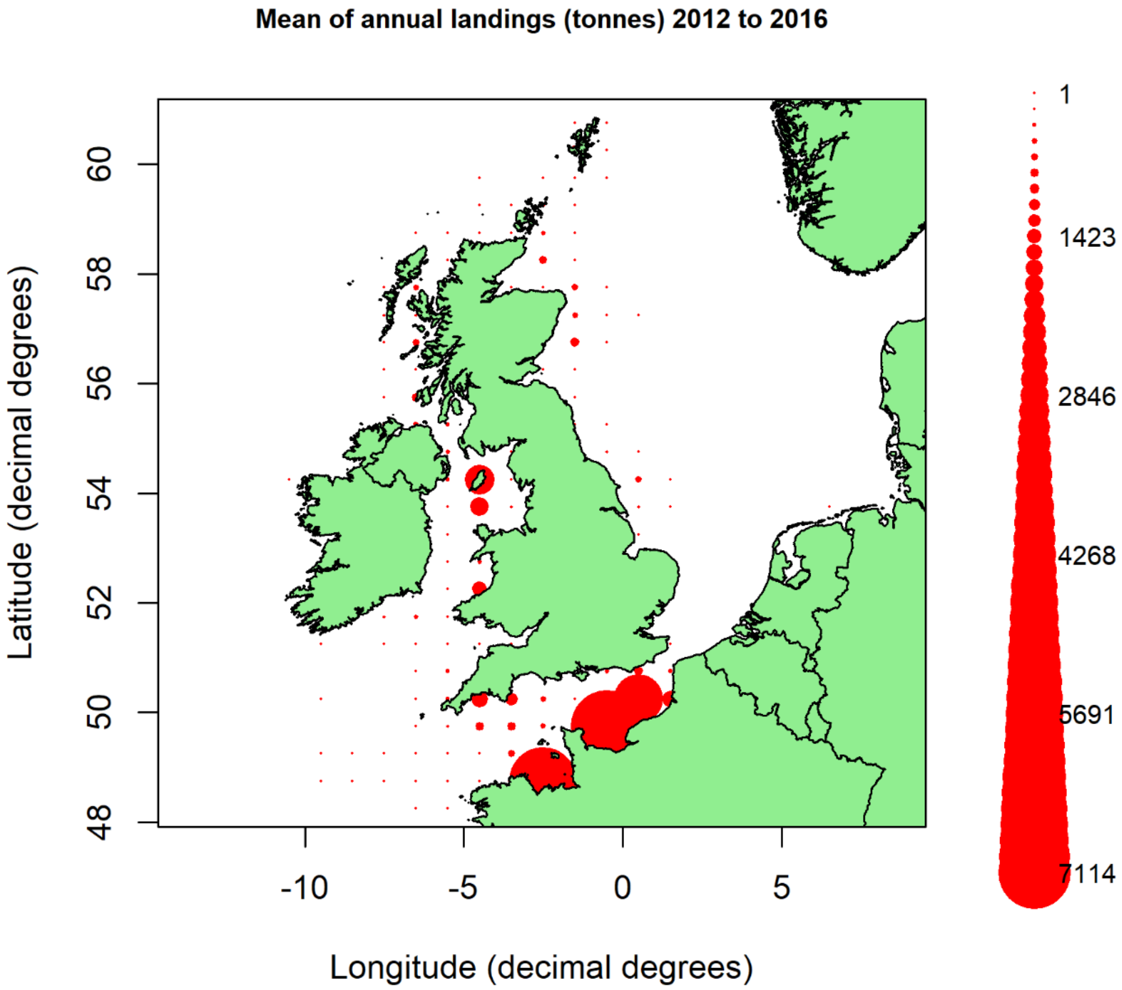


Figure 1.3: Map of the mean annual landings of king scallops (tonnes, live weight) by ICES statistical rectangle from the years 2012 to 2016, in areas around the British Isles. Each red point denotes the centroid of a single ICES statistical rectangle. ICES rectangles with mean landings less than one tonne have been excluded so that the map focusses on areas of substantial landings only. These landings include all nations fishing in these areas and the full range of gear types with reported scallop landings (i.e. not restricted to dredges). These landings were obtained from STECF (2018) and were not restricted to those landed in to UK ports. The green areas are land. The size of the points corresponds to magnitude of mean landings as indicated in the figure legend.

Scallops (all species) were the third most valuable wild-caught seafood animals landed in to ports in Wales by UK vessels in 2018 (£2.4 million, first sale value) (MMO 2019). Despite this relative high value, landings in to Wales have decreased since a peak in 2012 (Figure 1.4). King scallop beds are known to occur in four major areas in Wales, based on interviews and consultations with local scallop fishers (Figure 1.5). Of these areas, there is genetic evidence suggesting that the Cardigan Bay population is isolated from the other Welsh king scallop areas (Hold et al in press). However, biophysical modelling suggests that Cardigan Bay is a sink for larvae from both the Llyn Peninsula area and Tremadog Bay (Hold et al in press). Therefore, the degree of isolation of these populations in Wales remains unclear.

Table 1.2: The number of vessels in the UK (and Isle of Man) scallop dredge fleet in 2017, arranged by administrative port and vessel length category. Data obtained from Seafish.

Home Nation	Administrative Port	Length 0-10m	Length 10–12m	Length 12-15m	Length 15-20m	Length 20-24m	Length 24-40m	Length 40-60m
Scotland	Aberdeen	0	0	1	0	0	0	0
Scotland	Ayr	0	0	2	8	7	15	1
Northern Ireland	Belfast	11	7	6	8	1	1	0
England	Brixham	4	7	7	2	2	3	0
Scotland	Buckie	0	0	0	0	1	2	0
Scotland	Campbeltown	3	1	4	2	0	0	0
Isle of Man	Douglas	7	1	13	10	0	0	0
Scotland	Eyemouth	0	0	0	1	0	0	0
England	Fleetwood	0	1	1	0	0	0	0
Scotland	Fraserburgh	0	0	1	1	0	0	0
England	Grimsby	9	1	0	0	0	0	0
England	Hastings	15	1	4	1	0	0	0
Scotland	Kirkwall	0	1	1	0	0	0	0
Scotland	Lerwick	9	4	4	1	0	0	0
England	Lowestoft	4	0	6	0	0	0	0
Scotland	Malaig	0	0	1	0	0	0	0
Wales	Milford Haven	2	0	3	0	0	0	0
England	Newlyn	3	3	3	0	0	0	0
England	North Shields	1	2	3	2	0	0	0
Scotland	Oban	1	0	0	10	1	0	0
Scotland	Peterhead	0	0	1	1	1	0	0
Scotland	Pittenweem	4	0	0	0	0	0	0
England	Plymouth	6	2	2	1	0	0	0
England	Poole	20	1	3	0	0	0	0
England	Scarborough	1	1	0	0	0	0	0
Scotland	Scrabster	0	1	0	0	0	0	0
Scotland	Stornoway	1	0	3	5	0	0	0
Scotland	Ullapool	0	0	1	0	0	0	1
UK	Total	101	34	70	53	13	21	2

The following sections detail how scallop fisheries monitoring may be conducted, how scallop stock size may be estimated, the environmental impacts of scallop fishing and how scallop stocks may be managed.

1.2 Fishery Monitoring

Fishery-independent data

Fishery-independent data are not derived from the normal fishing behaviour of the fleet and are typically collected by scientific surveys on research vessels, and are often called indices (Gunderson 1993). For example, the Isle of Man (IoM) and Wales annual scallop surveys are conducted from the RV Prince Madog (Bloor et al 2017; Delargy et al 2019). Typically scallop fishery-independent surveys will use some combination or selection of dredging, trawling and optical methods to sample the stock in question. The type of vessel used, the number of stations sampled, the frequency and the stratification type are all important factors to consider when conducting a fishery-independent survey, and many different combinations of these features are used through the world's scallop fisheries (Table 1.3). Indices are important for analysing a fish stock, as they are often considered to provide unbiased and balanced sampling due to the scientific design and standardisation of the sampling methods (Murray et al 2013; Pennino et al 2016). Unbiased sampling of a fish stock is important for understanding the true stock structure through space and time, however surveys can be biased if they fail to sample the entire stock through space and time (Hilborn and Walters 1992). The inability to entirely sample a stock through space and time is reasonably common, as fishery-independent surveys tend to be expensive and therefore restricted to short periods of time and limited areas (Hilborn and Walters 1992; Murray et al 2013;

Pennino et al 2016). However, bias can be minimised by sampling as much of the stock range as possible using standardised methods alongside random or stratified-random sampling (Murray et al 2013; Smith and Hubley 2013; Hartill and Williams 2014). Stratified-random sampling involves dividing the wider survey area in to smaller areas, where fish densities are likely to be more homogeneous than across the entire area of the survey, and then sampling locations are randomly selected within these smaller areas (Hilborn and Walters 1992). The use of some level of stratification over entirely random or systematic sampling often improves precision and reduces variance on survey estimates, as both entirely random and systematic sampling have a risk of missing troughs or peaks in stock densities (Hilborn and Walters 1992; Smith and Hubley 2013). Systematic designs are where survey stations are positioned at regular intervals (Stokesbury et al 2004).

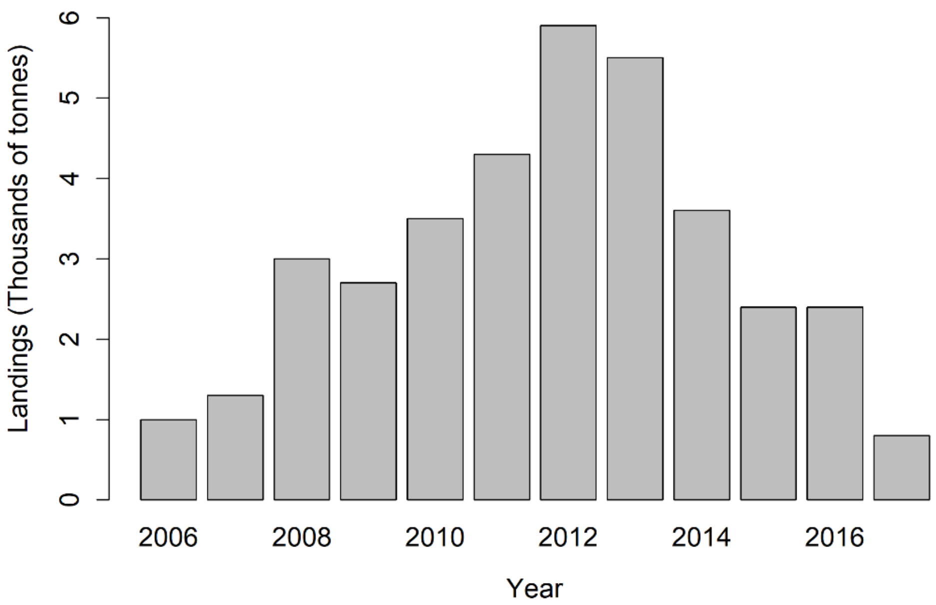


Figure 1.4: Landings of scallops in to Wales by UK vessels (MMO 2016; 2018).

Large areas where scallops aggregate, which can support a commercial fishery, are called fishing grounds, and within these fishing grounds high density areas are known as beds, and these beds will also have varying patchiness of densities within them (Brand 2016). These various levels of aggregations, combined with limited movement of individual scallops, mean that scallop distribution is non-random and predictable (Gustafson and Goldman 2012). Therefore, the sampling design of scallop surveys is important to ensure high precision of survey indices (Smith and Hubley 2013). A random survey design poses the risk of sampling, or not sampling, dense patches of scallops by chance, which increases the chance of overestimating variance on survey indices (Murray 2013; Smith and Hubley 2013; Hartill and Williams 2014). This in turn, is likely to lead to an overestimation of variance on stock assessment outputs based on indices (Smith and Hubley 2013). Systematic designs have been favoured for their simplicity in implementation and statistical analyses in some cases (Stokesbury et al 2004), however over large areas systematic surveys may miss aggregations of scallops which have a greater chance of being sampled using a stratified-random approach (Hilborn and Walters 1992). Stratified-random approaches have been shown to reduce variance of the mean survey indices by 20 – 28 % for the Canadian east coast sea scallop survey (which previously used a random design) (Smith and Hubley 2013). The type of stratification used in stratified-random surveys varies between scallop fisheries, with stratification by habitat type or commercial catch rates particularly popular (Table 1.3).

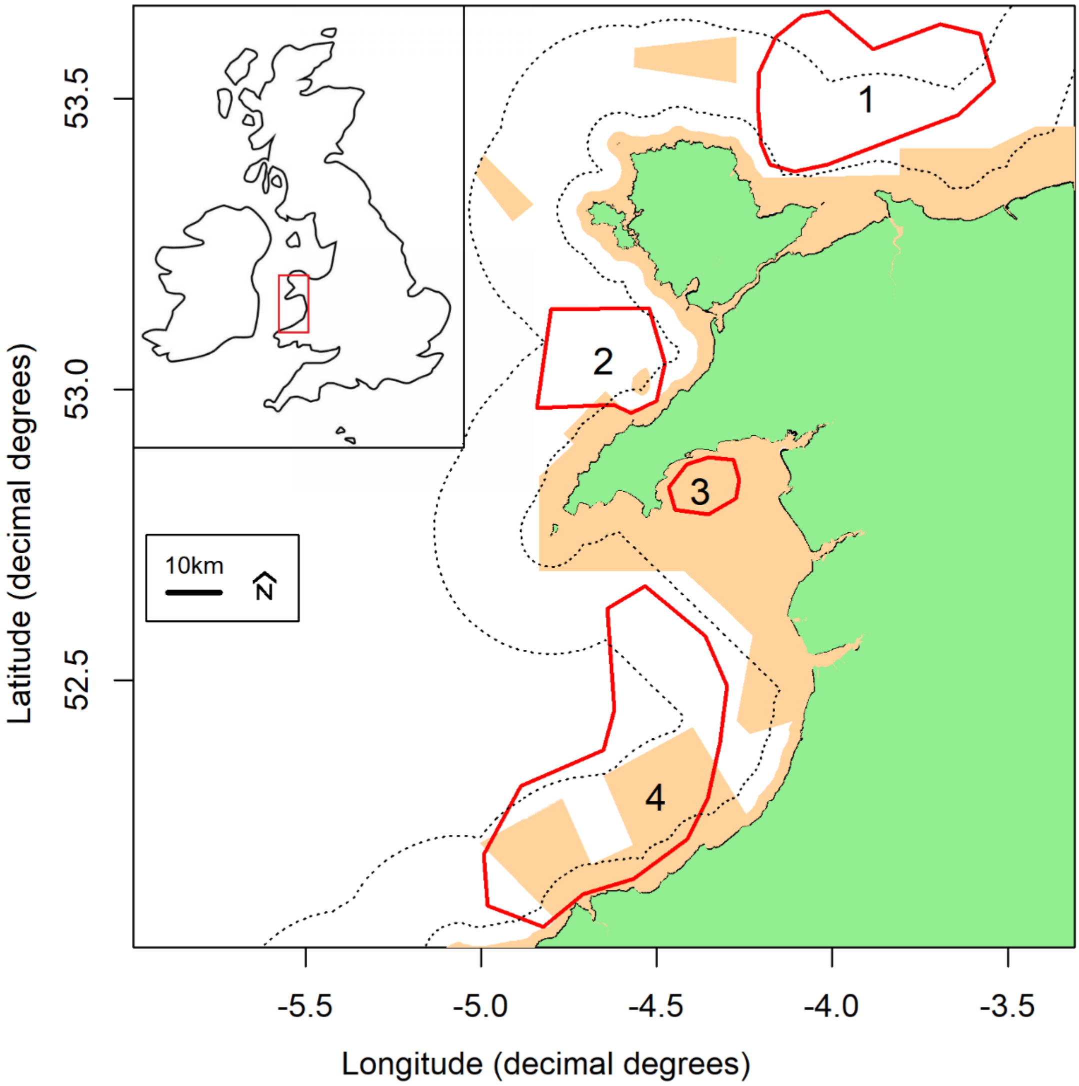


Figure 1.5: A map of king scallop areas around the Welsh coast, as determined using local fisher knowledge. King scallop areas are outlined in red and numbered as; 1) Liverpool Bay, 2) Llyn Peninsula, 3) Tremadog Bay and 4) Cardigan Bay. Green is land, orange is areas of sea closed to scallop commercial dredging and white areas are sea open to commercial scallop dredging. Dashed lines are the 3 and 12 nautical mile lines from shore. The inset map depicts the location of the fishing grounds within the British Isles.

Fishery-independent indices are often expensive to obtain, resulting in costs to the fishery or to government (Murray et al 2013; Hartill and Williams 2014). As a result, many surveys are not conducted as frequently as required, not conducted in all areas within the fishery or not conducted to the same intensity between years (Hartill and Williams 2014). These differences in surveys lead to bias and the ability to draw comparisons between surveys becomes weakened (Hilborn and Walters 1992; Hartill and Williams 2014). The key considerations for survey consistency include sampling the same locations and sampling with the same hauling speed and temporal haul length (Hartill and Williams 2014). Many scallop surveys have routinely sampled the same stations during each survey to ensure comparability between years, despite no commercial scallop fishing occurring in the locations anymore (e.g. Kangas et al 2011; Murray 2013; Dobby et al 2017; ICES 2018). By standardising these aspects of survey design, changes in indices between years should reflect changes in the scallop population. However, it is possible that the sampling gear may miss patches of scallops in some years (due to precision error) despite intending to sample the same location. It is also possible scallops may move over time, but there is limited evidence of mass migrations in the majority of scallop species (Brand 2016).

Table 1.3: Information on the fishery-independent surveys conducted in global scallop fisheries

Fishery	Vessel type	Method	Number of sampling locations	Sampling location selection	Primary output(s)	Reference
Isle of Man (IoM) king (*Pecten* maximus) and queen (*Aequipecten opercularis*) scallop	Research	Dredge and optical	~50	Fixed locations with additional added over time based on fishing grounds	Relative abundance and population structure. Stock assessment model parameters.	Bloor et al 2017
Scotland king scallop	Research or Commercial	Dredge	~80	Fixed locations stratified by sediment and fishing grounds	Relative abundance and population structure. Stock assessment model parameters.	Dobby et al 2017
East Canada sea scallop (*Placopecten magellanicus*)	Commercial	Dredge	>100	Stratified-random by catch rates or sediment type	Distribution and size structure. Stock assessment model parameters.	Jonsen el al 2009; Hervas et al 2013; Hubley et al 2014
US sea scallop	Commercial	Dredge and optical	~93	Stratified-random	Total meat weight per haul and whole animal size structure. Stock assessment model parameters.	Aldous et al 2013; Kelly et al 2011
France king scallop	Research	Dredge	~170	Stratified-random by recruitment rates from previous survey	Exploitable biomass index.	ICES 2018
Wales king and queen scallop	Research	Dredge and optical	~77	Stratified-random by sediment and management zones	Exploitable biomass, recruits and population structure. Stock assessment model parameters.	Lambert et al 2014; Delargy et al 2019
Eastern Australia saucer scallop (*Amusium balloti*)	Commercial	Trawl	200	Stratified-random	Relative abundance and size structure.	Jebreen et al 2008
Western Australia saucer scallop	Commercial	Trawl	90	Random	Relative abundance by recruits and harvestable scallops	Kangas et al 2011
New Zealand scallop (*Pecten novaezelandiae*)	Commercial	Dredge	Many, varies within sections of the fishery	Stratified-random by strata or fishing patterns	Population structure, distribution and absolute abundance of harvestable scallops. Some measures of recruitment.	Williams et al 2010; 2014
US weathervane scallop (*Patinopecten caurinus*)	Research	Dredge and optical	~50	Systematic design from random starting position	Relative abundance and population structure.	Gustafson and Goldman 2012
Iceland scallop (*Chlamys islandica*)	Commercial	Optical	120	Fixed stations	Absolute abundance.	ICES 2018

The timing of fishery-independent towed gear surveys is important, as differences in growth rates between the survey time and the fishing season need to be accounted for and failure to do so can bias stock assessment outputs (Hilborn and Walters 1992; Hartill and Williams 2014). It has also been shown that surveys in the spring are most effective at sampling queen scallops, up to a 42 % increase in queen scallops caught, because lower water temperatures cause a decrease in swimming escape responses (Jenkins et al 2003). In the Australian saucer scallop fisheries, it has been demonstrated that both fishery-independent indices and commercial catch rates of saucer scallops during the day are 39 – 57 % lower than those at night (Kangas et al 2011).

The majority of scallop surveys use dredges or trawls (Table 1.3). However, optical fishery-independent surveys provide an alternative way to sample scallop populations from towed fishing gear. Video surveys are a common technique used in the US sea scallop fishery because this species tend to lie on the seabed (Stokesbury et al 2004). Video surveys can provide information on scallop density and shell size (Aldous et al 2013). Camera surveys have been used in the US sea scallop fishery survey since 1999, and now multiple systems are used (Stokesbury et al 2016). One system is a drop-down camera, and another is a towed optical system (Stokesbury et al 2016). Scallops in this fishery have also been sampled using an autonomous underwater vehicle (AUV) fitted with a camera which is capable of estimating scallop abundance and measuring shell height (Walker et al 2016). AUVs have also been successful at estimating scallop abundance in Iceland scallop fisheries (Singh et al 2013). Furthermore, AUVs can also be used to detect dredge scars on the seabed indicative of fishing effort (Walker et al 2016). Towed optical surveys have been conducted in Cardigan Bay, Wales, alongside dredging to investigate the correlation between abundance estimated through dredges, stills and video (Lambert et al 2014). Improvements to the field of view and to the analysis of video and still images have occurred over time and correlation between still images, videos and dredges have also improved (Lambert et al 2014). Similar work has been conducted in the US weathervane scallop fishery with a camera sled used to assess gear catch efficiency (Gustafson and Goldman 2012) and cameras may be used to estimate the stock size in the future (NPFMC 2014).

Fishery-dependent data

Fishery-dependent data are obtained from normal commercial fishing activities in a variety of ways (Table 1.4). Fishery-dependent data carry several assumptions and biases compared to fishery-independent indices (Harley et al 2001; Beukers-Stewart et al 2003). Fishery-dependent data do not provide balanced sampling of the stock, as fishers are typically focussed on maximising catches and target areas of high density whilst trying to avoid low density sites (Hartill and Williams 2014; Pennino et al 2016; Shepperson et al 2016). Commercial catch rates are, therefore, unlikely to be able to detect all decreases in abundance, as fishers may move to a new aggregation of scallops when catches begin to decrease (Hilborn and Walters 1992; Hartill and Williams 2014). Similarly, catch rates do not account for closed areas within a fishery where proportions of the stock are protected (ICES 2013). Catch rates are also often reported from multiple vessels, which can lead to influences other than abundance affecting the rates such as differences between vessels, gears, operational practices, areas, seasons and discarding practices (Murray et al 2013; Thorarinsdottir et al 2013). These influences can often lead to apparent hyperstability of scallop stocks, where catch rates remain high despite a decline in stock biomass (Hilborn and Walters 1992; Murray et al 2013; Hartill and Williams 2014).

Logbooks or Vessel Monitoring Systems (VMS) are typical fishery-dependent data sources which can span the scale of the fishery (Pennino et al 2016). Logbooks, or any other form of submitting catch records, are typically gathered to provide information on catch rates and total landings from an area (Murray et al 2013). However, catches may lack detailed information or be subject to reporting errors (Pennino et al 2016). VMS are also used in several scallop fisheries, with legislation often enforcing the use of the systems on-board vessels at sea (ICES 2016). VMS sends an electronic ping which provides a vessel's position and speed, and typically these pings are sent out every 2 hours (ICES 2016). VMS is often used for enforcement, but can be used to estimate fishing effort (Murray et al 2009; Murray et al 2013). The vessel's speed is often used to estimate fishing activity, with particular speeds indicating whether a vessel is fishing or steaming (Murray et al 2013; ICES 2016). VMS is a requirement for all fishing vessels 12 m or greater in length from EU nations, and England, Scotland and Wales are introducing VMS to vessels less than 12 m in length by 2021.

Table 1.4: Uses of different types of fishery-dependent data in scallop fisheries

Data type	Examples of scallop fisheries used in	Purpose
Total catch or landings	IoM king *(Pecten maximus*) and queen scallop (*Aequipecten opercularis*) (Bloor et al 2017), Scottish king scallop (Dobby et al 2017), Celtic Sea king scallop (ICES 2013), the East Canada sea scallop (*Placopecten magellanicus*) (Jonsen et al 2009; Caddy et al 2010), France king scallop (ICES 2013), Shark Bay saucer scallop (*Amusium balloti*) (Kangas et al 2011), Patagonian scallop (*Zygochlamys patagonica*) (Pottinger et al 2006), Eastern Australia saucer scallop (Flood et al 2014), Iceland scallop (*Chlamys islandica*) (ICES 2013), US sea scallop (Aldous et al 2013)	To quantify total removals by fishing from stock
Logbooks or equivalent	IoM queen scallop (Murray et al 2009a; Andrews et al 2010), Shetland king scallop (Hervas et al 2011; Dobby et al 2012), Celtic Sea king scallop (ICES 2013), the East Canada sea scallop (Jonsen et al 2009; Caddy et al 2010), France king scallop (ICES 2013), Shark Bay saucer scallop (Kangas et al 2011), Patagonian scallop (Pottinger et al 2006), Eastern Australia saucer scallop (Flood et al 2014), Iceland scallop (ICES 2013), US sea scallop (Aldous et al 2013)	Primarily to assess and estimate catch rates (Murray et al 2013)
VMS or equivalent	IoM queen scallop (Murray 2009a; Andrews et al 2010), Faroese queen scallop (Thorarinsdottir et al 2013), Celtic Sea king scallop (ICES 2013), East Canada sea scallop (Jonsen et al 2009; Caddy et al 2010), France king scallop (ICES 2013), English Channel king scallop (ICES 2013)	As proxy for fishing effort or for enforcement (Murray et al 2009; Murray et al 2013)
On-board observers	Shetland king scallop (Howell et al 2003; Hervas et al 2011; Dobby et al 2012; Tindall et al 2016), Celtic Sea king scallop (ICES 2013), Patagonian scallop (Pottinger et al 2006) US sea scallop (Aldous et al 2013) and US weathervane scallop (*Patinopecten caurinus*) (Free-Sloan 2007; NPFMC 2014)	To gather data such as weight, size, age and maturity, as well as enforcement. Additionally, validation of logbook entries (Kangas et al 2011).
Port side observers	East Canada sea scallop (Jonsen et al 2009; Caddy et al 2010), Patagonian scallop (Pottinger et al 2006), Scottish king scallop (Dobby et al 2017), Celtic Sea king scallop (ICES 2013)	To gather data such as weight, size, age and maturity, as well as enforcement. Additionally, validation of logbook entries (Kangas et al 2011)
Processor observers	Shetland king scallop (Hervas et al 2011), Shark Bay saucer scallop (Kangas et al 2011)	To gather data such as weight, size, age and maturity, as well as enforcement. Additionally, validation of logbook entries (Kangas et al 2011)

To overcome reporting errors in logbooks, fishery observers can be placed on commercial fishing vessels, in markets or in processors to subsample catches, but this reduces the range of sampling through the human power required to conduct this type of sampling (Pennino et al 2016). These observers will typically record weight, size, age and other measurements from a subsample of the catch to better understand the biological structure of the target stock. Observations can also be used to validate logbook entries (Kangas et al 2011).

The use of fishery-dependent catch rates to estimate a proxy for abundance is an alternative to fishery-independent surveys due to the high costs associated with obtaining fishery-independent indices (Murray et al 2013; Hartill and Williams 2014). However, the validation of catches is vital if they are to be used as a proxy for abundance. Murray et al (2013) compared scallop fishery-independent survey indices against catch rates estimated from both logbooks and VMS to assess the strength of the relationship between such data types. The authors found the relationship to be strong between both types of fishery-dependent data and fishery-independent indices at the start of the fishing season, but the relationship became weaker as the stock depleted throughout the season (Murray et al 2013). The Shark Bay saucer scallop fishery had a strong correlation between fishery-independent survey indices and fishery-dependent catch rates up until 1995, at which point increases in commercial fishing intensity occurred (Kangas et al 2011). Since 1995 catch rates have overestimated the biomass in the fishery and this has highlighted the need for a more detailed assessment methodology using multiple data sources (Kangas et al 2011). As illustrated by these examples, fishery-dependent catch rates do not always correlate well with fishery-independent catch rates (Harley et al 2001; Beukers-Stewart et al 2003).

1.3 Estimating stock size

Fisheries monitoring data are often used to calculate a relative or absolute estimate of the size of the target stock (Hilborn and Walters 1992). Such evidence is important to inform management of the status of the stock and often can be used to provide biological reference points which can be used in target setting or to limit fishing activities to avoid overfishing of stocks (Jensen and Marshall 1982; Caddy 2004; Shertzer et al 2008). A typical reference points is B_{MSY}, which is defined as the biomass of the stock if the maximum sustainable yield (MSY) was harvested under typical recruitment conditions (NPFMC 2014). The MSY is defined as the greatest amount of biomass that could be removed from the stock through fishing over a long temporal scale (Maunder 2008; NPFMC 2014). Another typical reference point is F_{MSY}, which is the annual fishing mortality rate (F) required to catch the MSY (NPFMC 2014). Other variants of these or other types of reference point can be determined, which can be used to set fishing effort limits which serve as a proxy for how much biomass will be removed from the stock. There are many kinds of reference points used in fisheries throughout the world and many are used to suit the specific needs of the fishery in question.

Biological reference points are typically estimated using stock assessments (Caddy and Mahon 1995). Stock assessments have been used for over a century due to the economic importance of fisheries (Shertzer et al 2008). A wide range of stock assessment methodologies have been used in scallop fisheries (Table 1.6). Stock assessment methodologies may not necessarily estimate stock size but the majority do. Hilborn and Walters (1992) list four general approaches for conducting stock assessment with a view to estimating stock size: (1) direct observations (catches, counts or indices); (2) historical stock reconstruction from fisheries monitoring data; (3) mark-recapture or ratio change methods; and (4) depletion estimators. These approaches are discussed through the following sub-sections. An exception is (3), as these approaches assume that marked individuals are able to remix themselves with the unmarked population (Southwood and Henderson 2009) which is an unsuitable assumption for scallops due to their limited movement. Therefore, this particular approach is not discussed in this thesis.

Several other considerations of scallop stocks are important for stock assessment. Many stock assessment models assume constant fishing mortality throughout the spatial distribution of the stock, which is not the case in semi-sedentary species if fished in a rotational fashion (Hart 2003). In addition, benthic invertebrates, such as scallops, have been shown, in some cases, to exist as self-recruiting, isolated populations which makes them vulnerable to overfishing

(NPFMC 2014). Therefore, scallop fishery models often require attention to the spatial implications of analyses (Hart 2001). Similarly, it is often difficult to define a stock unit, and conducting a stock assessment without doing so is likely lead to error in estimations (Andrews et al 2010; Andrews et al 2013; ICES 2016). Defining a stock unit is important so that data can be grouped together that correspond to individuals with similar life histories, and accurately reflect the stock dynamics. These errors in estimations can arise through assuming that a stock is closed when in fact the stock size is influenced by other populations (Begg et al 1999). Combined genetic and hydrodynamic modelling studies are typically required to address the stock unit size for scallops (e.g. Elfstrom et al 2005a; 2005b; Kenchington et al 2006; Hold et al 2013; Salomonsen et al 2015; Hold et al in press).

Recruitment in wild fish stocks is extremely variable and difficult to predict (Shertzer et al 2008). Scallops are no exception (Cryer 2001a; Vause et al 2007; Flood et al 2014) and this variability makes them particularly vulnerable to overfishing, as an overfished stock cannot be guaranteed to be replenished each year through births (NPFMC 2014). The high variability in recruitment, and high variability in growth rates of scallops, results in highly variable catches and stock sizes between years in the majority of scallop fisheries, as well as a dependence on the recruitment of large cohorts (Caddy and Gulland 1983; Cryer 2001a; ICES 2016). Scallop recruitment is likely to be governed by a mixture of factors including environmental conditions and the size of the spawning stock biomass (SSB) (Smith and Rago 2004; Neill and Kaiser 2008; Thorarinsdottir et al 2013; NPFMC 2014). The relationship between the SSB and recruitment is referred to as a stock-recruit relationship (Iles 1994). A stock-recruit relationship is a common way to predict recruitment for fisheries, but it is a source of debate of whether it is appropriate to do so (Iles 1994). However, the relationship between stock size and recruitment is unknown for many scallop species, including king scallops (ICES 2016).

Environmental factors such as water currents, sea level and sea temperature have been used alongside stock size in recruit models for the Shark Bay saucer scallop fishery, but with mixed results (Joll and Caputi 1995; Lenanton et al 2009; Kangas et al 2011). Relationships between recruitment and variables such as sea temperature (Caputi et al 1996), water currents (Shephard et al 2010) and spat settlement (Beukers-Stewart et al 2003) have been shown in other works for specific scallop fisheries. The relationship between sea surface temperatures and recruitment has also been explored for king scallop fisheries throughout the British Isles, yet despite some significant results the relationship was not consistent (ICES 2016). The effect of the North Atlantic Oscillation (NAO) on recruitment was found to be significant and negatively correlated in some areas, however the relationship was inconsistent across the entire geographical range of the study (UK, Isle of Man and Ireland) (ICES 2016). This significant relationship in some of these areas was likely to be due to spat survival and production being disrupted by warmer winters and cooler summers associated with the NAO (ICES 2016). The effect of environmental influences on recruitment have also been shown to be highest when biomass is lowest, highlighting the need to maintain high biomass in stocks (ICES 2016). However due to the high variability, inconsistencies in results and some dispute over the driving factors, scallop recruitment relationships are largely unknown (NPFMC 2014; ICES 2016). Due to the unknown nature of scallop recruitment, the Canadian Browns Bank sea scallop stock assessment model allows recruitment to behave randomly (DFO 2013).

Annual natural mortality rate (M) is of considerable importance to stock assessments, as this determines the amount of the stock that will be removed through non-fishing deaths. Natural mortality is notoriously difficult to quantify, as fishing and natural mortality quickly become confounded in an active fishery (Hilborn and Walters 1992; Hewitt and Hoenig 2005). The two main techniques used to estimate natural mortality are from tag data (Hearn et al 1998; Frusher and Hoenig 2001; Latour et al 2003) or predictions from life history, such as growth parameters (Chen and Watanabe 1989;

Jensen 1996; Lorenzen 1996). However, it is also common to use estimates of natural mortality from other fisheries or species in stock assessments (Hewitt and Hoenig 2005). The range of annual natural mortality rates in scallop stock assessments ranges from 0.09 to 0.5 yr^{-1} (Table 1.5). In most cases these estimates are independent of time and scallop age and size. However, size-specific natural mortality has been tested in the US sea scallop stock assessments, where natural mortality was a function of shell height. The natural mortality rate of juvenile scallops was set to half the natural mortality rate of adult scallops (0.5 M), and then the natural morality rate increased gradually with scallop sizes until reaching the natural mortality rate at adult size (M) (NEFSC 2014). The Georges Bank stock assessments showed improved fits to survey data using this approach to modelling natural mortality compared to stock assessment model runs using size-independent natural mortality rates (NEFSC 2014).

Table 1.5: Natural mortality estimates used in scallop stock assessments

Fishery	M estimate used	Derivation of M	Reference
East Australia saucer scallop	0.09	Tagging data	Campbell et al 2012
Canadian Georges Bank sea scallop	0.1	Review of multiple techniques to estimate M.	Jonsen et al 2009
Scottish king scallop	0.15	Based on species with similar longevity.	Dobby et al 2017
Isle of Man king scallop	0.15	Sensitivity test of stock assessment models.	Allison 1993
US Georges Bank sea scallop	0.16 (0.24 for largest size class)	Stock assessment model sensitivity analysis.	NEFSC 2014
Isle of Man queen scallop	0.2	Review of multiple techniques to estimate M and stock assessment model sensitivity analysis.	Murray 2013
US Mid-Atlantic sea scallop	0.2 (0.3 for largest size class)	Stock assessment model sensitivity analysis.	NEFSC 2014
Coromandel New Zealand scallop	0.5	Review of multiple techniques to estimate M.	Williams et al 2010

Direct observations to estimate abundance

Many fisheries use direct observations such as survey indices or commercial catch rates to estimate relative stock abundance or absolute stock abundance (Table 1.6). Estimations of relative abundance requires standardisation of observations to ensure the relative scale is accurate, whereas estimates of absolute abundance require knowledge of the absolute efficiency of the observation method (Stokesbury et al 2004). Catch efficiency of towed gears is the fraction of target species that are retained compared to that which occurs in the path of the towed gear (Miller et al 2019).The Coromandel New Zealand scallop fishery assessment does not use fishery-dependent catch rates as a measure of relative biomass because the relationship between the two is not proportional (Cryer 2001b; Williams et al 2010). Instead the fishery analysts estimate absolute biomass by scaling survey indices using knowledge of the absolute efficiency of the dredge gear (Williams et al 2010).

Optical methods can also provide direct observations for estimating abundance. Capture efficiency of optical methods can be close to 100%, which is considerably better than towed gears, and this can result in higher accuracy estimates of abundance in the path of the camera (Stokesbury 2002). Absolute abundance of sea scallops has been routinely estimated using a drop-down digital image systems in the US, with absolute abundance of the total survey area estimated using the mean density of sea scallops from video samples taken in the area (Stokesbury 2002; Stokesbury et al 2004). This camera system is now able to measure shell height of the scallops, detect greater numbers of juvenile sea scallops, and the absolute abundance methodology accounts for both the selectivity and efficiency of the method to determine absolute numbers and biomass of sea scallops in the images (Carey and Stokesbury 2011; Bethoney and Stokesbury 2018). Scallops in this fishery have also been sampled using an AUV fitted with a camera which is capable of estimating scallop abundance and measuring shell height (Walker et al 2016). AUVs have also been successful at estimating scallop abundance in Iceland scallop fisheries (Singh et al 2013) and may be suitable for estimating shell size with future research (Singh et al 2014). Furthermore, AUVs can also be used to detect dredge scars on the seabed indicative of fishing effort (Walker et al 2016).

Depletion estimators

Catch rates from defined areas can also be used in depletion estimators to estimate stock abundance and the absolute efficiency of scallop fishing (Hilborn and Walters 1992; Beukers-Stewart et al 2003; ICES 2016). These models quantify how removals of target individuals affect the catch rate of the population when an area is repeatedly fished (Hilborn and Walters, 1992; Walter et al 2007). The semi-sedentary nature of scallops permits the use of such models as the animals are not thought to be able to relocate from fished areas (Kangas et al 2011). These types of models have been used in the Western Australia Shark Bay saucer scallop (Kangas et al 2011), Isle of Man king scallop (Beukers-Stewart et al 2001), US sea scallop (NEFSC 2001; Walter et al 2007) and the Canadian Bay of Fundy sea scallop (Hervas et al 2013).

Historical reconstruction stock assessment models

Fisheries scientists have been developing mathematical representations of the growth, recruitment and mortality of fish stocks for over a century (Shertzer et al 2008). The development of computing power through time has allowed these mathematical models to be applied to large fisheries data sets and allowed the utilisation of statistical methodology designed to account for high variability in fisheries monitoring data and high uncertainty in model calculations (Hilborn and Walters 1992; Pauly et al 2002; Maunder and Punt 2013).

The historical reconstruction model approach estimates the initial stock size and then uses a mathematical model to estimate the abundance in consequent years in the time series (Hilborn and Walters 1992). The parameter values in the calculations are then adjusted to provide the best fit between observed and estimated data sets from the fishery (Hilborn and Walters 1992). In modern stock assessments, this requires statistical methodology and is often computed using a likelihood function (Maunder and Punt 2013). However, the resultant model estimates of the stock are often subject to both observation error and process error as a result of the stochastic nature of fish populations (Jonsen et al 2009). Process error is the natural variation in the stock dynamics, and differs from observation error which is the error in the methodology (Ahrestani et al 2013). Quantification of the uncertainty around stock assessment model estimates is key to appropriately reflecting the confidence management should have in model outputs, and a wide range of statistical methodologies exist to quantify the uncertainty (Jonsen et al 2009). Bayesian statistical methods for parameter estimation and quantifying uncertainty are popular in fisheries stock assessment models, as they can address non-linearity in equations more efficiently than other approaches and observation and process errors can be accounted for simultaneously (McAllister and Ianelli 1997; Jonsen et al 2009).

Although the statistical and computational methodology (software or estimation algorithm) for implementing stock assessment models can vary considerably, many of the mathematical approaches can be broadly classified based on their approach to structure the reconstructed stock in the calculations. Structuring the stock involves grouping the estimated stock by some common characteristic, such as age or size. The structure of the estimated stock is highly important, with examples highlighting differences in estimation of key pieces of evidence based on the modelled stock structured (e.g. Townsend 1986; Massey et al 2006; Tahvonen 2009). The most commonly used structuring approaches can be defined as unstructured models, delay-difference models, age-structured methods and size-structured methods. The following sub-sections details historical reconstruction stock assessment methods by their simulated stock structure.

Unstructured models

Unstructured, surplus-production or biomass dynamic models are simple models which are relatively easy to apply (Jensen and Marshall 1982; Jensen 2005). Unstructured models estimate total biomass or harvestable biomass as a single value driven by parameters such as mortality, growth and recruitment and do not incorporate any further stock structure (Prager 1992; Jensen 2005; Shertzer et al 2008; Tahvonen 2008). The parameters can be estimated from effort and catches which are often straightforwardly obtainable for fish stocks (Jensen and Marshall 1982). Various forms of unstructured models have been developed over time which make varying assumptions about whether a fish stock should be assumed to be in equilibrium or not (Prager 1992; Jensen 2005). One of the most well-known options is the logistic-type Schaefer (1954) unstructured model, of which further extensions have been developed (Hilborn and Walters 1992). The predictive power of unstructured models has been shown to be close to that of more complex structured alternatives in some cases (Ludwig and Walters 1985; 1989; Moxnes 2005). However other studies, which have compared the performance of unstructured models against more detailed models, have found the predictive power of unstructured models to be weaker in terms of either statistical fit or estimation of key outputs such as abundance or survey indices (Townsend 1986; Massey et al 2006; Jonsen et al 2009). Due to their simplification of stock processes, unstructured models have been deemed to be too rudimentary to accurately model fish stocks and are often only used when more detailed data are not available (Townsend 1986; Quinn and Deriso 1999; Tahvonen 2009). However, unstructured models are favoured by fishery economists for estimating fish stock size due to their simplicity (Deacon 1989; Brown 2000; Wilen 2000) but have been widely criticised in biological studies (Townsend 1986; Quinn and Deriso 1999; Tahvonen 2009).

Delay-difference models

Delay-difference models typically separate the stock into two groups representing immature and mature individuals (Shertzer et al 2008) and have greater estimation power than unstructured models by addressing factors such as mortality, growth and recruitment as separate parameters for each of the groups (Jonsen et al 2009). The two-group approach of delay-difference models is also useful for a fishery with an enforced minimum landing size (MLS), where the groups can be divided by their size relative to the MLS. A MLS is a management tool which dictates the smallest size of a species which may be sold (Cochrane 2002; Stergiou et al 2009). Multiple Canadian sea scallop fisheries are assessed using Bayesian delay-difference models (Smith and Lundy 2002; O'Boyle 2002; Jonsen et al 2009; Smith et al 2009; DFO 2013; Hervas et al 2013). These models estimate historical and current values of fishing mortality and stock biomass to create stock projections (Hervas et al 2013). The delay-difference model in the Canadian Browns Bank fishery was compared with the previously used unstructured model and found to correlate better with survey indices and catches (DFO 2013).

Table 1.6: Types of analytical techniques for stock assessment in scallop fisheries

Analytical Method	Advantages	Disadvantages	Fisheries used in
Direct use of commercial catch rates for relative or absolute abundance	Requires less data and less detailed data. Is likely to be the cheapest option and with the least processing time. Often used if recruitment is highly variable. Does not depend on time series.	Relationship between indices or catch rates and true values can be weak (Cryer 2001b; Williams et al 2010). Alternative modelling approaches often estimate additional information.	Southern New Zealand scallop (Williams et al 2014), French Bay of Seine king scallop (ICES 2013), Icelandic scallop (ICES 2013), Patagonian scallop (Pottinger et al 2006), US weathervane scallop (Gustafson and Goldman 2012; NPFMC 2014), Western Australia Shark Bay saucer scallop (Kangas et al 2011) Southern Australia Bass Strait commercial scallop (Harrington and Semmens 2010).
Scaling of survey indices	Not biased by commercial fishing patterns as commercial catch rates are. Analytically simpler than modelling methods. Does not depend on time series.	Requires detailed understanding of sampling gear efficiency. Often requires extensive sampling of stock. Alternative modelling approaches often estimate additional information.	US sea scallop (Bethoney and Stokesbury 2018).
Depletion estimators	Can be applied to entire scale of fishery. Additionally estimates absolute catch efficiency. Does not depend on annual time series.	Linear technique has many assumptions which are often violated (Rago et al 2006). Linear estimates are sensitive to nature of depletion fishing pattern (Rago et al 2006).	Western Australia Shark Bay saucer scallop (Kangas et al 2011), Isle of Man king scallop (Beukers-Stewart et al 2001), US sea scallop (NEFSC 2001; Walter et al 2007) and Canadian Bay of Fundy sea scallop (Hervas et al 2013).
Unstructured, surplus-production, production, biomass dynamics (all alternative names for same model type)	Simple time series models which are relatively easy to apply (Jensen and Marshall 1982; Jensen 2005).	Simplification of stock processes may make them too rudimentary to accurately model fish stocks (Townsend 1986; Quinn and Deriso 1999; Tahvonen 2009). Requires time series.	Coromandel New Zealand scallop (Williams et al 2010).
Delay-difference	Likely to have greater estimation power than unstructured models (Jonsen et al 2009).	Potentially weaker biological estimation power than age-structured models (Bjorndal and Brasao 2006; Smith et al 2008). Requires time series.	Canadian sea scallop (Smith and Lundy 2002; O'Boyle 2002; Smith et al 2009; Jonsen et al 2009; DFO 2013; Hervas et al 2013), Isle of Man queen scallop (Murray et al 2013).
Age-structured	Can have greater estimation power than other methods (Bjorndal and Brasao 2006; Smith et al 2008).	Large amount of fine detail required for implementation (Jonsen et al 2009). Lack of suitable data can lead to inconsistent biomass estimates (Jonsen et al 2009). Requires time series	Scottish king scallop (Dobby et al 2017), Eastern Australia saucer scallop (Campbell et al 2012; Flood et al 2014)
Length-structured	Used when sufficiently precise age data is not available, and many classes are still desired (Lai and Gallucci 1988).	Can be more complex to implement than other approaches. Requires time series.	US sea scallop (Aldous et al 2013), Coromandel New Zealand scallop (Williams et al 2010).

The Canadian Georges Bank model uses three size-classes, as opposed to the typical two, and was compared to the previously used virtual population analysis (VPA) and an unstructured model (Jonsen et al 2009). VPA models are fully age-structured and follow cohorts through time (Pope 1972; Shertzer at al 2008; Jonsen et al 2009). The delay-difference model was deemed to produce better estimates of annual stock biomass than the unstructured model or VPA, the latter of which was hampered by a lack of suitable age data (Jonsen et al 2009). The IoM queen scallop fishery has used the Catch-Survey Analysis (CSA) model, which is free and available to download (Murray 2013; NOAA 2014). The CSA model is a delay-difference model, and the two stages are defined in the IoM stock assessment as below and above the MLS implemented in this fishery (Murray 2013). The CSA model has previously produced suitable estimates of stock biomass when compared to an unstructured model (Cadrin 2000).

Age-structured models

Age-structured models estimate the stock in age-classes, which can allow for greater accuracy in overall biomass estimates through the capture of important biological dynamics between age-classes (Bjorndal and Brasao 2006; Smith et al 2008). Various kinds of age-structured models exist; however, a large amount of fine detail is required to be able to successfully implement them and obtain accurate results (Jonsen et al 2009). VPA is an age-structured approach which simulates reductions in cohorts of fish with time based on losses through mortality using the Baranov catch equation applied in backward time (Baranov 1918; Pope 1972; Shertzer et al 2008). The backward application of the Baranov catch equation begins with an estimated abundance of the eldest age-class, and uses age-specific fishing and natural mortality rates to estimate the abundance of each next youngest age-class in a stepwise fashion (Pope 1972; Shertzer et al 2008).

More detailed and statistical age-structured models are known as statistical catch-age (SCA) models, and these typically differ from VPA by assuming error in catches and applying the Baranov catch equation in forward time (beginning with the youngest age-class) (Shertzer et al 2008). A major advantage of the forward approach is that it becomes far simpler to adjust the Baranov catch equation to account for the specific dynamics of individual fish stocks, such as accounting for seasonality in mortality rates (Shertzer et al 2008). Due to advances in computational power and computational statistical applications, the complexity and detail of SCA models has increased with time and led to fields such as integrated analysis (IA) models (Maunder and Punt 2013). IA models are capable of modelling multiple observed data sets simultaneously using a joint likelihood function, and this results in an efficient stock assessment model which is able to account for, and quantify, high degrees of uncertainty (Maunder and Punt 2013). It should be noted that sophisticated statistical models, such as IA models, are not restricted to age-structured analyses: less biologically detailed models, such as unstructured and delay-difference models, can be implemented as IA models.

Assessments of the Scottish king scallop stocks are conducted using an age-structured model, named Time Series Analysis (TSA) (Dobby et al 2017). The model is an IA model and uses age-structured landings, discards and survey indices (Dobby et al 2017). The model also has the ability to account for data deficient years in a long time series (ICES 2016; Dobby et al 2017). Prior to the first use of the TSA in 2011, the stock was assessed using a VPA model (Dobby et al 2012). The TSA model was chosen to replace the VPA model because the TSA can better account for poor years of data and because the TSA allows for parameters, such as fishing mortality, to change in controlled fashion, as well as providing prediction intervals (Bayesian equivalent of confidence intervals) for outputs such as stock abundance and mortality (Dobby et al 2012). The Eastern Australia saucer scallop fishery compares biomass estimates using two models, one of which is a fully age-structured, Bayesian IA model (Campbell et al 2012; Flood et al 2014). The model uses a temporal increment of one month and it estimates MSY (Campbell et al 2012).

Size-structured models

Size-structured models, often termed length-structured models, can be used when sufficiently precise age data are not available for a fishery, and many classes are still desired to capture a high degree of biological reality (Lai and Gallucci 1988). Age-structured data may be unavailable due to the monitoring structures in place or because the target species is difficult or impossible to age (Sullivan et al 1990). A length-structured model may also be chosen when the observation error in aging is suspected to be high, as observation error in measuring the size of fish is likely to be lower than aging due to the relative simplicity of measuring a fish compared to aging (Sullivan et al 1990). Modelling a population by length-structure is often more complex than by age-structure because growth must be modelled explicitly, as animals can transition between stages in the stock within the (typical) period of an annual model time step (e.g. Punt et al 1997; Maunder 2001). It is important to note that modelling growth is a function of time and size, and therefore age or tagging data are required when estimating growth parameters.

The US sea scallop fishery is assessed every three years using a size-based, spatially explicit, IA model called CASA (Aldous et al 2013; NEFSC 2014). The model uses size-structured survey indices, landings, discards, size to meat weight relationships and growth ring size measurements to allow for the transition between size-classes in the model (Aldous et al 2013). Biological reference points are then estimated using a novel Stochastic Yield Model (SYM) which uses Bayesian methods to best account for parameter uncertainty and directly estimate B_{MSY} and F_{MSY} (Aldous et al 2013). The Coromandel New Zealand scallop fishery have used a length-based projection model in years where surveys were not conducted and other methods could not be implemented (Williams et al 2010). However, analysts studying this fishery have argued that estimating B_{MSY} is not appropriate for scallop stocks due to highly variable recruitment and growth rates (Williams et al 2014).

1.4 Environmental Impacts

Another key consideration for management is the environmental impact of scallop fisheries, and there is substantial pressure for legislation to reduce the environmental footprint of scallop fishing gear and practices (Stewart and Howarth 2016). Scallop dredges are regarded as one of the most damaging fishing gears to both the physical seabed and benthic communities (Collie et al 2000; Kaiser et al 2006; Stewart and Howarth 2016). The extent of the disturbance and damage varies with habitat type, level of natural disturbance, fishing pressure and the type of dredge used (Kaiser et al 1996). Toothed dredges are likely to have the greatest impact, because the teeth can penetrate as far as 10 cm into the seabed (Currie and Parry 1996; Kaiser et al 1996; 2000; 2006; Collie et al 2000; Murray et al 2009a; Andrews et al 2010; Hinz et al 2012; Stewart and Howarth 2016). However, trawling can also have a significantly negative impact on the seabed, and in some cases the recovery time can be as long as after dredging (Kaiser and Spencer 1996; Collie et al 2000; Kaiser et al 2002; Andrews et al 2010). Trawling is the primary gear used in queen scallop (Hall-Spencer et al 1999; Jenkins et al 2003), saucer scallop (Joll and Penn 1990; Kangas et al 2011) and Mediterranean scallop (*Pecten jacobaeus*) (Hall-Spencer et al 1999) fisheries. Towed gears can also have further negative impact on the scallop stock by damaging organisms which juvenile scallops settle on, creating a negative feedback loop (Beukers-Stewart and Beukers-Stewart

2009). The organisms juvenile scallops have been demonstrated to settle on include branching bryozoans, macroalgae and maerl beds (Howarth et al 2011; Stewart and Howarth 2016).

Physical seabed impacts

Impacts on the seabed by towed scallop fishing gears include changes to sediment composition and topography (Murray et al 2015; Stewart and Howarth 2016), which are considered to be negative (Beukers-Stewart and Beukers-Stewart 2009; Sciberras et al 2013). Seabed disturbance can lead to suspension and loss of sediment, leading to an increase in seabed roughness (Schwinghamer et al 1998; Murray et al 2015). Cobble and boulders can be displaced and troughs are often left in the seabed, however the extent of the damage is partly dependent on the environment (Eleftheriou and Robertson 1992; Murray et al 2015; Stewart and Howarth 2016). Different substrates experience different degrees of effect, with coarser substrates susceptible to greater levels of damage and having longer recovery periods than sand substrates (Collie et al 1997; Kaiser et al 2006; Malik and Mayer 2007). Biological habitats, such as *Modiolus modiolus* beds and other biogenic reefs, are particularly vulnerable and can be negatively affected by mobile fishing gear for substantial lengths of time (Kaiser et al 2000; Beukers-Stewart and Beukers-Stewart 2009; Murray et al 2009a; Andrews et al 2010; Stewart and Howarth 2016). Habitat complexity and structure can be quickly lost under intense fishing pressure from towed gears, resulting in degradation of biogenic reefs, loss of biodiversity and loss of ecological functioning (Eleftheriou and Robertson 1992; Currie and Parry 1999; Hall-Spencer et al 2003; Beukers-Stewart and Beukers-Stewart 2009; Morsan 2009; Murray et al 2009a; Andrews et al 2010; Aldous et al 2013).

The level of natural disturbance also affects the ability of an area to withstand and recover from the negative physical impacts of dredging (Beukers-Stewart and Beukers-Stewart 2009; Andrews et al 2010). Certain high energy environments are subjected to high levels of natural disturbance which may have a stronger effect on the seabed than fishing disturbances (Hinz et al 2010a; Stewart and Howarth 2016). Controversy has existed around this issue in the US sea scallop fishery. Some studies (Stokesbury and Harris 2006; LeBlanc et al 2015) have provided evidence that natural disturbances were stronger than the effects of dredging, however other studies have shown strong negative impacts from fishing gear (Collie et al 1997; Malik and Meyer 2007). It has also been noted that the type of damage caused by dredge teeth is different from that caused by water currents (Aldous et al 2013). Hinz et al (2010a) found no sign of dredge marks on the seabed seven months after a complete closure of the Cardigan Bay Special Area of Conservation (SAC), Wales, to commercial scallop dredging and concluded that the natural disturbance had a stronger influence on the seabed than dredging. A follow up study found evidence of dredge marks, after fishing had been allowed for two months, but concluded that natural disturbance had a stronger effect upon the level of disturbance (Hinz et al 2010b). A later study was conducted in this SAC, which involved dredging different lanes at different fishing intensities and conducting surveys before and after the dredging (Murray et al 2015). It was found that dredge scars were visible in all dredging lanes two weeks after the dredging had been conducted, but after four months the dredge marks were gone from the lanes dredged at the lowest intensities (Murray et al 2015). The lanes were then surveyed 10 months later to find only two out of the 17 lanes had dredge marks which were still visible (Murray et al 2015). The conclusion was therefore drawn that some intensities, sediment types and depths may not be able to recover over a 10-month closed season, although the vast majority did (Murray et al 2015).

Epifauna impacts

Epifauna are animals living on the seabed and include species of hydroids, bryozoans, sponges, corals, crustaceans, starfish, molluscs and more (Steele et al 2010). Changes to the seabed can cause long term effects on the epifaunal community (Collie et al 1997; Kaiser et al 2006; Murray et al 2015) and these effects are an important conservation concern (Beukers-Stewart and Beukers-Stewart 2009). Epifauna are important to the ecosystem as they create structures which can be used for settlement by a variety of species, including juvenile scallops (Hall-Spencer and Moore 2000; Lambert et al 2011). Benthic epifauna are especially vulnerable to towed gears because they lack the ability to move out the way (Ramsay and Kaiser 1998; Stewart and Howarth 2016). Smaller species tend to be more resilient than upright, fragile species which can easily be damaged by towed gears (Collie et al 2000; Kaiser et al 2000; Andrews et al 2010; Stewart and Howarth 2016). For example, taxa such as encrusting bryozoans can recover far quicker than slow-growing sponges (Kaiser et al 2006). Studies conducted around the IoM have shown a reduced amount of upright species as a result of dredging but even small, fast-growing species have shown significant differences in abundance between fished and unfished areas (Andrews et al 2010). Hinz et al (2012) conducted a fishing experiment around the IoM and found significant decreases in brittlestar (*Ophiura ophiura*) abundance in fished areas compared to unfished control areas. The study also found significant increases in scavenging species which were deemed to be taking advantage of discard mortality from the towed gears (Hinz et al 2012).

Shifts in community structure have also been shown to be caused by dredging, with predominantly small-bodied organisms being found and a decrease in biodiversity occurring after dredging has taken place (Kaiser et al 2000; Lambert et al 2011). However, dredging is not always the primary driver of community shifts, with the species composition of some areas thought to be caused by natural disturbances. Lambert et al (2011) found fishing to be the most significant driver in reducing the maximum size of epifauna, during an area comparison study conducted in IoM waters. However, wave stress was found to be the prominent cause of a reduction in epifauna biomass with fishing frequency playing a secondary roll (Lambert et al 2011). Similarly, several studies have assessed the recovery of the Cardigan Bay SAC since closure to commercial scallop dredging. Hinz et al (2010a) compared species composition to a closed area in England and found little difference, prompting the argument that dredging was not responsible for the community structure in the SAC. Other studies have compared the closed area to an open area within the SAC over different time scales since the closure, and all found no significant differences in epifaunal community composition between the two areas (Hinz et al 2010b; Albrecht 2013; Sciberras et al 2013). This led all three of these studies to conclude that the high natural disturbance levels in the area have led to a high disturbance tolerance within the SAC.

Lambert et al (2017) investigated how various levels of scallop dredge fishing intensity affected the epifaunal community in an experimental setting in the Cardigan Bay SAC. It was shown that some sessile epifauna (cnidarians, bryozoans) were reduced by 39 to 70 % in areas in the experiment which were fished at an intensity between 1 and 3 (an intensity of 1 meaning the area swept by the scallop dredges was equal to the size of the area). They also found a two- to four-fold increase in scavenging species such as epifaunal echinoderms in areas fished greater than an intensity of 2 (Lambert et al 2017). Despite these statistically significant findings, the authors agreed with previous studies and concluded that the natural disturbance in the area was similar in magnitude to fishing intensities greater than 6, based on analysing benthos from unfished control areas in the experimental design.

Infauna impacts

Infauna are animals living within the seabed and include species of hydroids, bryozoans, corals, crustaceans, molluscs, polychaeta (bristle worms) and more (Truett and Johnson 2000). In comparison to epifauna, little is known about the effects of scallop fishing upon infauna (Stewart and Howarth 2016). Infauna are also vulnerable to scallop dredging as the teeth can penetrate as much as 10 cm below the seabed (Currie and Parry 1996; Kaiser et al 1996; Stewart and Howarth 2016). It is presumed that infauna which are able to escape the direct impact of a dredge will still be at risk from being suspended in the water column or being crushed in the sediment (O'Neill et al 2013; Stewart and Howarth 2016). Some studies have shown a variety of relationships between the effects of dredging and infauna taxa (Stewart and Howarth 2016). Kaiser et al (2000) found dredging reduced infauna biomass in IoM waters, but O'Neill et al (2013) observed no difference in infauna diversity and abundance between fished and unfished sites in waters in west Scotland. Currie and Parry (1996; 1999) showed that dredging in Australian waters resulted in the flattening of callianassid shrimp mounds, but recovery was observed by six months. Lambert et al (2017) found a significant two- to four-fold increase in scavenging infaunal crustaceans (predominately families Upogebiidae, Cirolanidae and Mysidae) in areas which were fished at an intensity greater than two, during the fishing experiment in the Cardigan Bay SAC.

Bycatch

Dredge and otter trawl fisheries also catch a range of non-target species, or bycatch (Andrews et al 2010). Bycatch is a significant issue in many fisheries, and studies show that modifying towed gears can reduce bycatch rates by as much as 64 % in some cases (Hall and Mainprize 2005; Harrington et al 2005; Pottinger et al 2006). Overall mortality of bycatch has been estimated from an Irish Sea scallop survey at 20 – 30 % of all bycatch caught (Shephard et al 2009). The type of fishing gear also influences the type of bycatch caught, with trawl fishing for queen scallops in the IoM shown to catch more finfish species than dredges (Andrews et al 2010). Dredge fisheries have been shown to catch high numbers of dogfish; however, some dogfish species have a high survival rate (average 78 to 98 %) and so catching these species is less of a concern (Rodriguez-Cabello et al 2001; Revill et al 2005). Hinz et al (2012) found dredges caught significantly more bycatch than otter trawls in a study conducted in the waters of the IoM. In the US sea scallop fishery, bycatch primarily consists of flatfish species and regulations have been put in place by management to reduce bycatch (Andrews et al 2010; Aldous et al 2013; Stewart and Howarth 2016). The bycatch caught in the Patagonian scallop fishery is less than 10 % of the total weight of the catch (Pottinger et al 2006).

Fuel and emissions

Another important environmental impact of fishing is the emission of greenhouse gases (GHG) from the burning of fossil fuels used to power fishing vessels (Driscoll and Tyedmers 2010). The use of fuel also has economic considerations, as burning more fuel will cost more money. Therefore, from both an environmental and economic perspective it is beneficial to minimise fuel consumption relative to the amount of target species landed. A term used to describe the ratio of fuel consumption to catch or landings is fuel intensity (litres of fuel expended to catch a tonne of target species), and this is highly correlated with GHG emissions per tonne of target species caught (Driscoll and Tyedmers 2010). Parker and Tyedmers (2015) estimated median global fuel intensity of dredges to be approximately 500 l per tonne of landings, and the median for any gear used to harvest molluscs to be approximately 800 l/tonne. The average is higher for all gears targeting molluscs than dredges as trawls and pots and traps are used in some mollusc fisheries (Parker and Tyedmers 2015). The global median for dredges was therefore less than those for pots and traps (> 2,500 l/tonne), bottom trawls (> 1,500 l/tonne), hooks and lines (approximately 1000 l/tonne), similar to gillnets and pelagic trawls (approximately 500 l/tonne), but greater than surrounding nets (< 500 l/tonne) (Parker and Tyedmers 2015). Pots and traps, gillnets, bottom trawls and pelagic trawls had at least one fishery harvesting molluscs in the study (Parker and Tyedmers 2015). The global median for harvesting molluscs was less than those for harvesting crustaceans (> 2,500 l/tonne), flatfish (> 1,500 l/tonne), large pelagic species (approximately 1,000 l/tonne), similar to salmonids and other finfish (approximately 800 l/tonne), whilst greater than those for harvesting small pelagic species (< 500 l/tonne) (see Parker and Tyedmers 2015 for details of these classifications). From these findings it is evident that either using dredges or harvesting molluscs are not the least fuel-efficient gears or targets, nor the best, of wild fisheries. Nevertheless, it remains important to understand and quantify fuel intensity, and consequently GHG emissions, for specific fisheries if these fisheries wish to better evaluate their impacts on climate change (Driscoll and Tyedmers 2010).

1.5 Fisheries management

The management of a fishery is fishery-specific and dependent on factors including data availability, financial resources and specific goals (Tindall et al 2016). Implementing fishery management often involves the use of various management tools or regulation measures. Like many fisheries, scallop fisheries can be regulated through catch limits, effort limits, a MLS, temporal restrictions, spatial restrictions, gear restrictions and vessel restrictions. The aims of the measures are typically to reduce fishing effort or reduce the amount of target species that may be caught so that biological reference points may be met (Cochrane 2002). These kinds of regulatory measures can be used in combination and vary from fishery to fishery, with the successfulness of different approaches also varying (Table 1.7).

Catch limits and MLS

Catch limits are a method to reduce the amount of target species removed from the stock and are often based on management reference points, which are typically estimated from some form of stock assessment or quantitative fishery model (Kirkwood 1981; Shertzer et al 2008). Catch limits are often referred to as a total allowable catch (TAC), and can be divided into quotas for each vessel, regions or nations (Copes and Charles 2004). Alternatively, a TAC is set for the entire fishery and the vessels able to exploit this TAC are controlled through licencing (Copes and Charles 2004). Typically, a TAC is set for the entire fishing season, but can also be set on other timescales such as daily, weekly or monthly limits. Temporal TACs are often quoted as total biomass, number of animals or meat weights that can be fished (Copes and Charles 2004). Setting a TAC has been done in scallop fisheries such as the Patagonian scallop (Pottinger et al 2006), the USA weathervane scallop *(*NPFMC 2014) and the Iceland scallop (ICES 2013) fisheries.

The East Canada sea scallop fishery is also managed using a TAC and managers look to check catch rates against long-term historical averages, in an attempt to govern the fishery (Caddy et al 2010; DFO 2013). Likewise, the US sea scallop fishery introduced a TAC for each separately managed zone within the fishery (Aldous et al 2013). Each vessel received a quota of the TAC set for each zone, in total meat weight (Aldous et al 2013). The IoM queen scallop fishery is also governed using a TAC (Andrews et al 2010). If the TAC is exceeded, then the extra is deducted from the following year's TAC (Andrews et al 2010). The IoM government also have the right to close the fishery at any point if the TAC is excessively overshot (Andrews et al 2010). Furthermore, the TAC can only be increased when the long-term biomass trend is also increasing and this helps remove any uncertainty regarding annual fluctuations (Andrews et al 2010). The Coromandel and Northland New Zealand scallop fisheries set catch limits as meat weights for the entire season, where in the past the vessels were subjected to daily catch limits (Cryer 2001a; Williams et al 2010). These fisheries use an individual transferrable quota (ITQ) system to allocate a proportion of the TAC to individual vessels (Williams et al 2010). The benefit of ITQs for fishers is the ability to sell or trade unused or unwanted quota to other fishers (Copes and Charles 2004), and ITQs are discussed further in the Vessel Restrictions sub-section of this thesis. Daily weight limits are still used for recreational fishing in other parts of the wider New Zealand scallop fishery (Twist et al 2015). Limits on daily meat weights are also used in the Tasmanian commercial scallop fishery (Mendo et al 2014), as well as the Abrolhos Islands and Mid-West Trawl Managed, and the Shark Bay, saucer scallop fisheries, both Western Australia (Flood et al 2014). Management can stop the taking of scallops if the daily limit is exceeded in these Australian fisheries (Flood et al 2014).

In some scallop fisheries proxies for catch rate limits have been used instead of a TAC. The Shetland king scallop fishery, Scotland, is governed by monitoring landings per unit effort (LPUE) rates, and areas within the fishery can be closed if the LPUE rates drop below a pre-defined level (Tindall et al 2016). Similarly, the Victoria commercial scallop fishery, South Australia, can be closed if the average meat weight per scallop falls below a pre-defined level (Flood et al 2014). These management techniques are practical as fishers often move on from areas when catch rates or meat weights are not high enough (Tindall et al 2016).

The capture of the target species can also be controlled through the use of a MLS, which typically restricts the sale of individuals below a specified size (Cochrane 2002; Stergiou et al 2009). The benefit of this approach is to attempt to protect smaller, and often younger individuals, so that they can reproduce and contribute offspring to the stock before they are removed by fishing (Cochrane 2002; Stewart 2008). An additional benefit may also be that when eventually caught, the target species may be in a more valuable condition for the fishery. A MLS is enforced in many scallop fisheries (Table 1.7).

Temporal restrictions

Temporal restrictions are usually implemented to restrict fishing effort and/or allow the target stock and the wider ecosystem time to recover from the impacts of fishing. The closure of a fishery over many months is often referred to as a closed season. Closed seasons are typically used to attempt to allow the scallop stocks to recover in time for the next year, through the protection of juveniles from fishing gear (Stewart and Howarth 2016; Tindall et al 2016). The use of a closed season is common and occurs in multiple scallop fisheries (Table 1.7). The Abrolhos Islands and Mid-West Trawl saucer scallop fishery, Western Australia, uses closed and open seasons and place strict regulations on the opening of the fishing season (Flood et al 2014). The fishery doesn’t allow trawling until after the peak spawning event of the season and the length of the fishing period is determined by the catch allowance set (Flood et al 2014). The fishery, like the Western Australia Shark Bay saucer scallop fishery, also does not permit the season to open until estimated biomass is sufficiently high (Flood et al 2014). Closed seasons may not be successful in isolation as they can encourage increased effort levels in the open season, as fishers attempt to make-up catch that they have foregone during the closed season and reduction in catch is often not achieved (Hilborn and Walters 1992; O’Keefe et al 2013).

Spatial restrictions

Spatial regulations can be highly effective management tools for semi-sedentary species such as scallops which have restricted movements and relatively predictable distributions (Beukers-Stewart et al 2005). Spatial restrictions are typically used to protect parts of the target stock or wider ecosystem within a fishery, whilst leaving other areas open to commercial fishing. Spatial management is not independent of time, with temporary spatial closures, real-time closures and permanent area closures all used to prevent fishing in particular areas for particular periods (Stewart and Howarth 2016; Tindall et al 2016). As well as closing sections of fishing grounds for various periods of time, managers can also choose how the size of sections to close and these are often referred to as partial closures (Twist et al 2015). In addition to closing areas, spatial regulations can also designate areas for different levels of protection and activities. The implementation of spatial management in scallop fisheries has been very successful in several cases (Stewart and Howarth 2016). For example, the introduction of spatial management to the US east coast sea scallop fishery in 1994 took the fishery from the brink of collapse to being one the most valuable fisheries in the entire country (Hart and Rago 2006; Stewart and Howarth 2016). However, the link between closed areas and benefit to the wider fishery is not always evident. Closed areas have been argued to result in a loss of yield (up to 50 %) due to high natural mortality rates or high natural disturbance rates (Stokesbury et al 2007). In addition, closing an area of a fishery may result in a displacement of effort levels to parts that remain open, as fishers attempt to maintain catches in a smaller area (Stewart and Howarth 2016). This is likely to have negative effects on the target species and wider ecosystem (Hiddink et al 2006). Spatial management can also be highly controversial when multiple users of an area have very different views on the best use of the area (Sciberras et al 2013; Twist et al 2015).

Multiple types of spatial closes, whether temporary, permanent or indefinite, have been implemented in scallop fisheries (Table 1.7). Permanent closures of areas within a fishing ground can also be used to protect other features from negative impacts of scallop dredging or trawling. The Welsh and English Channel king scallop fisheries' waters have zones permanently closed to scallop fishing to protect important habitats, or other species, from dredging as their primary function (ICES 2013). Fully closing a fishery is understandably the most controversial with fishers (Sciberras et al 2013; Twist et al 2015) and partial closures were shown to result in significantly higher scallop densities (1.9-fold higher) in New Zealand than a marine reserve where a complete closure to anthropogenic activities was enforced (Twist et al 2015).

Rotational closure of areas within a fishery are a form of temporary and spatial closure which allows for the recovery of areas and protection of juveniles whilst fishing still persists in other areas (Stewart and Howarth 2016). This type of area management can follow the way scallop fishers typically fish, where they will move on from an area when catch rates decrease and would lead to inefficient, uneconomical fishing (Beukers-Stewart et al 2003; Tindall et al 2016). Rotational management is used in the Coromandel and Southern New Zealand scallop fisheries (Williams et al 2010; Williams et al 2014), the Chinese Yesso scallop fishery (Akroyd et al 2015) and the Commonwealth commercial scallop fishery, South Australia (Jebreen et al 2008; Holmes et al 2013). The US sea scallop fishery imposed a rotational closure system to protect densities of younger scallops with a view to significantly increasing scallop abundance. As a consequence, catch rates increased considerably in some areas (0.8 kg/tow to 9.7 kg/tow between 1997 and 2000) and there is evidence of overall greater mean weights of landed scallops and greater larvae export as a result (Hart 2003; Hart and Rago 2006; Aldous et al 2013). The use of rotational areas has also been considered effective in protecting the ecosystem as well as protecting sea scallops in this fishery (Aldous et al 2013).

Gear restrictions

Management can also place restrictions on the gear used for fishing to reduce the environmental impact of the gear, reduce effort and help regulate catch rates (Cochrane 2002). In the case of dredges this can involve regulation of the mesh size of nets, the diameter of dredge rings, the size and number of the teeth on the dredges, dredge width and the number of dredges a vessel can tow. Limiting the number of dredges limits the amount of effort that may be applied per haul. The majority of the other gear regulations are usually enforced to avoid catching scallops that are under the minimum landing size (MLS) and to help to avoid catching unnecessary bycatch species (Stergiou et al 2009). Gear regulations are common in scallop fisheries, with the specifics of regulations varying with the specifics of the fishery (Table 1.7).

Table 1.7: Summary of regulation approaches used in various scallop fisheries and indication of success

Fishery	Key regulations	Successfulness	Key reference
Patagonian scallop	TAC, closed areas and licences	Successful, Marine Stewardship Council (MSC) certified since 2006	Pottinger et al 2006
US weathervane scallop	TAC, closed season, closed areas, gear restrictions, mechanical shucking ban and limit on crew sizes	Not overfished	NPFMC 2014
Iceland scallop	TAC and full closure	Full closure since 2003	ICES 2013
Eastern Canada offshore sea scallop and Canada Full Bay sea scallop	TAC, temporary closures, spatial closures, licences	Regions MSC certified since 2010 and 2013	Caddy et al 2010; Hervas et al 2013
US sea scallop	TAC, temporal restrictions, spatial rotational closure, MLS and crew size restrictions	MSC certified since 2013	Aldous et al 2013
IoM queen scallop	TAC, temporal restrictions, spatial restrictions, MLS, gear restrictions and vessel restrictions	MSC certified in 2011 but since revoked	Andrews et al 2010
New Zealand scallop	Catch limits, closed season, temporal restrictions, spatial restrictions	Varied success throughout fisheries	Williams et al 2010; 2014
South Australia commercial scallop	Daily catch limits, spatial restrictions, spatial rotational management and temporary closures	Undefined	Flood et al 2014
West Australia saucer scallop	Daily catch limits, spatial restrictions, spatial rotational management and temporary closures	Deemed a mixture of environmentally limited and sustainable	Flood et al 2014
East Australia saucer scallop	Daily catch limits, Daily catch limits, spatial restrictions, spatial rotational management and temporary closures, MLS	Deemed sustainable	Flood et al 2014
Scotland king scallop	Spatial and temporary restrictions, gear restrictions	Shetland section MSC certified since 2011	Dobby et al 2012

Vessel regulations

As well as gear restrictions, vessels are often regulated within a scallop fishery. Restrictions can be placed on the total number of vessels permitted in the fishery, the maximum size of vessels, the number of vessels within particular size classes and the maximum power of vessels, with a view towards reducing effort and avoiding overfishing (Stewart and Howarth 2016). Generally, a licencing or permit system can be used to control the size and dynamics of the fishing fleet. The use of licencing is extremely common, and occurs in multiple scallop fisheries, however some variations around the use of licences and the degree of control occurs. For example, the US sea scallop fishery introduced licences to limit the number of vessels (Aldous et al 2013). However, licences were issued to all vessels currently active in the fishery, which resulted in too many vessels to allow for stock recovery and therefore other regulatory measures were required as well (Aldous et al 2013). The Scottish king scallop fishery uses licences, and no new licences are ever issued (Dobby et al 2012; Tindall et al 2016). Licencing can be a complicated issue depending on political structure of the fishery (Townsend 1990). The US federal government issues licences to fish for scallops in the Exclusive Economic Zone (EEZ) zone off Alaska, but the Alaska state fisheries management places in force further licences to control the vessels fishing weathervane scallops in Alaskan waters (Free-Sloan 2007; NPFMC 2014). When licences are coupled with catch limits to create ITQs they are generally considered an efficient way to harvest a fish stock, as fishing mortality can be controlled (Waters 1991). However, licenced fisheries using ITQs can encourage under-reporting of catch, overcapitalisation and rent-seeking behaviour, which are often detrimental to the target stock and small vessels (Kearney 2001).

Other vessel restrictions such as vessel length and power limits are used in fisheries such as the IoM queen scallop (Andrews et al 2010), Welsh king scallop (The Scallop Fishing (Wales) (No. 2) Order 2010) and other fisheries in EU waters (Dobby et al 2012). Further types of restrictions to vessels include a limit on trawling speeds in the Chinese Yesso scallop fishery (Akroyd et al 2015), limits on crew sizes in the US weathervane and sea scallop fisheries (Aldous et al 2013; NPFMC 2014) and a ban on mechanical shucking machines in the US weathervane scallop fishery (NPFMC 2014). The latter two restrictions are highly effective curbs on effort because the vessels in these fisheries carry out shucking (dissections of scallops to obtain meat) at sea (Aldous et al 2013).

Direct effort restrictions

Many of the tools detailed so far are designed to restrict fishing effort, however there are further tools which directly limit effort. One such restriction in scallop fisheries can include a ban on fishing at night in an attempt to reduce effort (Hervas et al 2011; ICES 2013; Tindall et al 2016). Other practiced management strategies are seen in the Bay of Seine, France, where there are restrictions on the number of hours per day that fishing can occur and the number of days per week (Tindall et al 2016). Similar measures have also been used in the Coromandel New Zealand scallop fishery, with a limit set at five days of fishing per week combined with daily hour restrictions (Cryer 2001a; Williams et al 2010). Likewise, the US sea scallop fishery brought in a restriction on the number of days at sea vessels can fish within a year to combat overfishing (Aldous et al 2013). The Chinese Yesso scallop fishery limits dredging to the five-day working week and combines this with a temporal restriction on dredge tow length set at 15 minutes (Akroyd et al 2015). UK vessels over 15m in length fishing for either king or queen scallops are restricted by the number of days that each vessel may fish in Western Waters Area VII for each quarter of the year (UK Government 2020).

Selecting management tools

This section has now summarised many of the tools that have been implemented in scallop fisheries to attempt to reduce catches or effort and avoid overfishing. However, it is difficult to quantify the exact impact a management tool, or combination of management tools, which has been applied in one fishery will have on another fishery. Management of fisheries is often case specific (Hilborn and Walters 1992), and although some studies have quantified effects of management tools on scallop yields or stock size, it is often challenging to separate these effects from natural fluctuations, changing environmental conditions, technological advances in the fishery or other management tools implemented at the same time. Future research may attempt to plug these gaps in our knowledge, but in the meantime the likely impact of a management tool can be best determined by fishery-specific modelling and simulations.

Using modelling and simulations to determine the best fishing strategy for a fishery is referred to as optimisation of harvesting tactics (Hilborn and Walters 1992) or harvest control rules (Deroba and Bence 2008). Harvest control rules are often a simple function specifying the amount of catch that should be taken, or effort or fishing mortality applied, based on the size of the stock (Deroba and Bence 2008). The optimisation of a harvest control rule is performed using a stock assessment model to simulate the stock under a range of scenarios, and a mathematical optimisation method is used to identify the scenario required to achieve a target or reference point (Hilborn and Walters 1992). One example would be to test the effects of changing the MLS in a fishery, where the fishing mortality rate in the fishery is directly related to the MLS. In this example, the optimisation method could test a single value of fishing mortality, corresponding to a MLS, in a stock assessment model using a broad range of stock sizes. The resultant output would indicate potential outcomes of adjusting the MLS under a wide range of stock sizes. This concept can be applied to many further types of management tools, such as spatial management strategies (e.g. Caddy and Seijo 1998; Hart 2006).

Testing and optimisation of harvest control rules were beyond the scope of this thesis, but are an important area of research for addressing the unknowns that exist in applying management tools to a fishery.

1.6 King scallop management in Wales

King scallops in Wales are currently managed using input controls such as gear and effort restrictions (The Scallop Fishing (Wales) (No. 2) Order 2010, Table 1.8), however none of these are linked to a stock assessment. This decrease in landings, combined with the commercial importance of the fishery, highlights the need for further evidence to support more effective sustainable management methods for this Welsh king scallop fishery.

Cardigan Bay in Wales represents a key component of the greater Welsh scallop fishery, and consequently a large quantity of scallop research has been conducted in this area (Figure 1.6) (Sciberras et al 2013; Lambert et al 2014; Lambert et al 2017). Cardigan Bay also contains a relatively large SAC (~960 km^2) in which commercial scallop dredging has been prohibited since June 2009 (Scibberas et al 2013). The combination of detailed historical data sets, the relative importance of this area to the wider Welsh king scallop fishery and the presence of an important closed area made this area of high interest, and therefore this thesis focussed on Cardigan Bay for all analyses (Figure 1.6).

1.7 Rationale for study

This thesis aimed to provide quantitative evidence, based on fisheries monitoring data, which could be used to support the sustainable management of Welsh king scallop populations and the environmental and economic impacts of fishing these. The thesis focussed on methodologies used to estimate two key pieces of evidence important for the sustainable management of the Cardigan Bay scallop fishery; the absolute size of king scallop populations in the area and the effect of a unit of fishing effort on both the target species and the wider ecosystem. These two pieces of evidence focus on two key aspects of sustainable fishing. The absolute size of the king scallop stock through time is extremely important for understanding the size of the resource at the centre of the fishery, and quantification of this allows for appropriate management strategies to be determined (Jensen and Marshall 1982; Caddy 2004; Shertzer et al 2008). The effect of a unit of effort from the fishing gear is also extremely important for understanding the impacts of fishing on the wider ecosystem, as well as the target species, and this in line with an environmental management plan.

Table 1.8: List of management controls specific to the Welsh king scallop fishery

Management control	Details	Area (distance from shore)
Vessel engine power limit	≤ 221 kW	1 – 12 nmi
Vessel size limit	≤ 10 m vessel length	1 – 3 nmi
Tow bar restriction	≤ 185 mm diameter	1 – 12 nmi
Tow bar restriction	≤ 3m length	1 – 3 nmi
Tow bar restriction	≤ 4 m length	3 – 6 nmi
Tow bar restriction	≤ 6.8 m length	6 – 12 nmi
Dredge restrictions	≤ 85 cm frame width; ≤ 150 kg weight; must have spring-loaded tooth bar; no diving plate; ≤ seven belly rings per row; ≤ eight teeth; ≤ 22 mm tooth width; ≤ 110 mm tooth length	1 – 12 nmi
Dredge number limit	≤ six dredges	1 – 3 nmi
Dredge number limit	≤ eight dredges	3 – 6 nmi
Dredge number limit	≤ 14 dredges	6 – 12 nmi
Minimum landing size	110 mm (shell width for this species, due to width greater than height)	1 – 12 nmi
Minimum landing size	100 mm (shell width for this species, due to width greater than height)	> 12 nmi
Temporal closure	1st May – 31st October annually	1 – 12 nmi
Spatial closure	Permanent	0 – 1 nmi
Spatial closure	Permanent	Cardigan Bay SAC

The thesis aimed to estimate king scallop absolute stock size using statistical historical reconstruction stock assessment models, a depletion model and additionally quantifying the absolute catch efficiencies of multiple commercial scallop dredgers, which could allow the scaling of catch rates to estimates of absolute abundance in the future. Additionally, it was aimed to better understand the importance and implications of stock assessment model estimated stock structure (unstructured, age-structured, and size-structured). This thesis also aimed to investigate the effect of vessel characteristics, fishing practices and sediment type on vessel catch efficiency. Furthermore, this work aimed to understand the impact of repeatedly dredging areas on king scallops, benthos and fuel consumption rates, with a view to towards an effort-based management approach considering trade-offs between multiple fishing efficiency objectives.

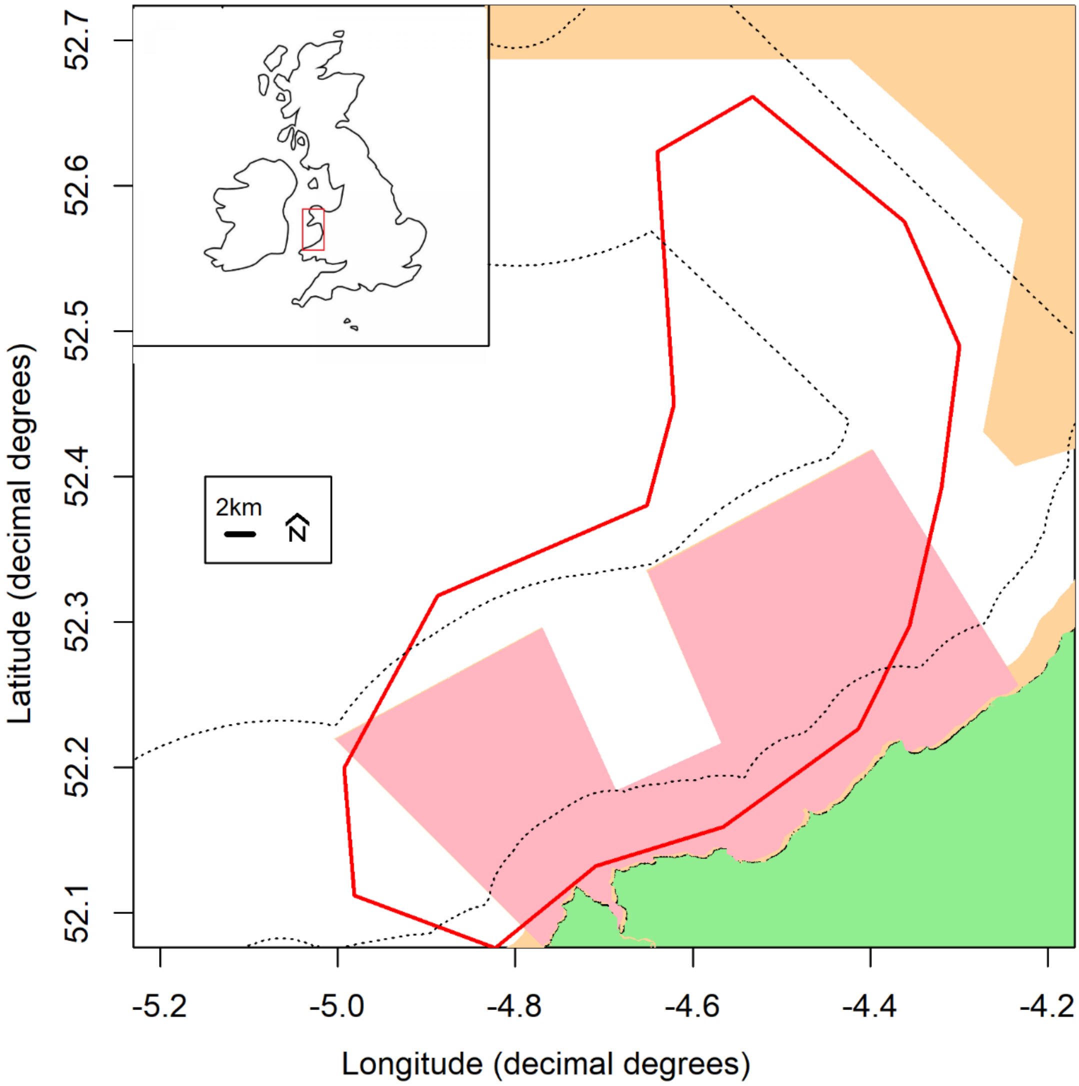


Figure 1.6: Map of the Cardigan Bay king scallop fishing ground. Green is land and white is area of sea open to king scallop dredging. Orange areas are closed to king scallop dredging. The pink area is the Cardigan Bay SAC, which is also closed to scallop dredging. The dashed lines are 3 and 12 nautical mile lines from the shore. The area outlined in red is the area surveyed by Bangor University on annual scallop surveys since 2012, which is 4,158 km^2. The black rectangle in the inset map indicates the location of Cardigan Bay within the British Isles.

In addition to these aims, the methodologies also aimed to estimate several other highly useful variables that could support management. These include, but are not restricted to, annual fishing mortality rates, annual recruitment and management reference points such as B_{MSY} and carrying capacity.

More specifically the objectives of the next four chapters were to:

1) Estimate the catch efficiency of five commercial scallop dredgers using a depletion model and investigate any variation in these catch efficiencies based on vessel fishing patterns, vessel characteristics and sediment. In addition, estimate the local abundance of king scallops within relatively small areas using the depletion model.
2) Highlight with simulations how a measure of environmental fishing efficiency and a measure of fuel efficiency are expected to change as areas are fished repeatedly. Support these simulations with empirical data and discuss why empirical patterns agree or disagree with simulated patterns.

3) Estimate annual stock size of a king scallop stock in Cardigan Bay, using age-, length- and un- structured IA stock assessment models. In addition, estimate research vessel catch efficiency, fishery selectivity, discard retention curves, fishery catchability, individual growth parameters, age- and length- weight parameters, age- and size-at-maturity, MSY, B_{MSY}, F_{MSY}, carrying capacity, annual fishing mortality rate and annual recruitment for this stock.
4) Investigate the effect of estimated stock structure on key model outputs, from the IA stock assessment models.

The implementation and comparison of methodologies will provide multiple options for future stock assessment for king scallops in Wales, and are likely to be applicable to other scallop fisheries. In addition, many of the estimated values will help provide understanding of the effects of scallop dredging on the target species and wider ecosystem. All work is expected to contribute towards the sustainable management of king scallops in Wales. The methodologies and findings are also likely to be of interest to other fisheries. The wide range of proposed estimated states, rates and parameters would be useful to other king scallop fisheries either directly or as prior distributions in stock assessments.

CHAPTER 2: VESSEL CATCH EFFICIENCY IS HIGHLY VARIABLE OVER SMALL SPATIAL SCALES

Abstract

Stock abundance can be estimated directly from industry-based survey catch rates, if variations in catch efficiency are understood. We estimated catch efficiencies and scallop densities from a depletion experiment using five commercial dredge vessels. Each vessel sampled pre-defined fishing lanes across a gradient of fishing intensities within an area closed to commercial scallop fishing. Catch efficiency for commercially sized scallops varied considerably between vessels, ranging from 0.13 to 0.62, and catch efficiency was also variable for individual vessels. The lowest catch efficiency was observed for the largest vessel, which fished at the fastest speeds, swept the most area per haul and had a small engine capacity relative to its size, all of which may help explain the low catch efficiency. Commercially sized scallop densities in each lane ranged from 25 to 59 per 100 m^2. These results highlight that the difference in catch efficiency estimates can be highly variable between vessels, and for the same vessel, over small spatial scales. Similarly, scallop densities can also vary considerably over small spatial scales. This work highlights that further research is required to understand variation in catch efficiencies to be able to scale industry-based survey catch rates to abundance.

2.1 Introduction

Global scallop landings have risen over the last 20 years (Stewart and Howarth, 2016) and king scallop landings have increased over the previous 50 years in the UK (2,500 tonnes in 1968 and 32,600 tonnes in 2017) (Beukers-Stewart and Beukers-Stewart 2009; MMO 2018). In 2017, scallops were the third most valuable fisheries in the United Kingdom and fifth most valuable in the United States (MMO 2018; NMFS 2018). The increase in landings and the relative value of scallops leads to a need for quantitative assessments of stock size to support sustainable management. The majority of assessed scallop stocks are carried out using fishery-independent indices obtained from a research vessel and time-series stock assessment models (e.g. NEFSC 2014; Nasmith et al 2016; Dobby et al 2017). However, although ideal for minimising sampling bias, using fishery-independent indices gathered by a single research vessel is not always feasible due to high costs of data collection and because time-series stock assessment models require multiple years of data (Murray et al 2013; Hartill and Williams 2014). An alternative approach is to use fishery-dependent catch rates, although few scallop stocks use these to directly estimate stock size because of the complex relationship with stock size (Williams et al 2014). However, using catch rates from multiple commercial vessels chartered to conduct a fishery-independent survey can be considered a cost-effective and suitable method to estimating stock size if either the catch efficiencies of the vessels are similar or the differences in catch efficiencies can be quantified (Maunder and Punt 2004).

Catch efficiency is the fraction of target species that are retained compared to that which occurs in the swept area of the towed gear (Miller et al 2019). Understanding catch efficiency is a significant problem for fisheries using towed gears as their catch efficiency is known to be highly variable (Fraser et al 2007). Catch efficiency varies between vessels through vessel characteristics, gear specifications and differences in gear operations (Byrne et al 1981). For example, a smaller, lighter vessel will roll and pitch more than a larger, heavier vessel, which may result in the gear losing contact time with the seabed (Byrne et al 1981). The engine capacity of a vessel determines the ability to maintain desired speed in strong tides, and vessel speed is known to affect catch efficiency (Fifas et al 2004). The speed and direction of the vessel in relation to the sea state and tidal flow affects both the contact time of the gear with the seabed and the mouth opening of the gear, and is determined by the crew (Carrothers 1981; Fifas et al 2004; Reiss et al 2006). Both the amount of contact time with the seabed and the width of the mouth of the gear affect catch efficiency.

King scallops (*Pecten maximus*) are bivalves that live partially buried in the seabed and, once settled, are known to be semi-sedentary (Howell and Fraser, 1984; Brand, 2016). In the UK, king scallops are typically fished using spring-loaded Newhaven dredges. Dredges are towed on bars (gangs) of three to twelve from each side of a vessel (Lart 2003). Each dredge consists of a spring-loaded toothed bar designed to allow for give when the gear encounters boulders. The toothed bar dislodges scallops such that they are caught in a chainmail bag (Boulcott et al 2014). The spring compression and the length, number and spacing of the teeth affect the ability to dislodge scallops and therefore affect catch efficiency (Lart 2003; Fifas et al 2004). The chainmail bag ring size and wear affect the number and size of scallops retained in the bag (Lart 2003). Operational differences between vessels such as length of warp used, spring compression and maintenance of the gear relate to the handling skills of the crew (Byrne et al 1981) and individual vessel catch efficiencies are expected to vary accordingly.

Catch efficiency of dredges is also known to be affected by sediment type. Dredge teeth penetrate further in gravelly sediments than in sandier ones (Szostek et al 2017) and this greater penetration is likely to result in increased catch efficiency, as the teeth dislodge king scallops more easily and reduce the gap between the seabed and dredge (Lart 2003). Changes in catch efficiency with ground type also occur in other scallop fisheries, with smooth and soft grounds producing higher estimates of catch efficiency compared with firm grounds or grounds with higher topographical variation (Buestel et al 1985; Currie and Parry 1999). Catch efficiencies on smooth, flat, muddy grounds were 12% higher than firm, sandy grounds with complex topography for Australian dredges targeting commercial scallops (*Pecten fumatus*) (Currie and Parry 1999). Complex topography is associated with recesses, in which dredges are likely to miss scallops (Currie and Parry 1999). Catch efficiency was also higher on gravelly sediments than sandy sediments for beam trawls (Creutzberg et al 1987), although these vessels do not typically target scallops.

One effective way to assess gear catch efficiency is through depletion estimation, i.e. by quantifying how removals of individuals affect the catch rate of the population when an area is repeatedly fished (Hilborn and Walters 1992; Walter et al 2007). It also allows estimation of initial density and local abundance and has been applied to a range of marine species (Gonzalez-Yanez et al 2006; Rago et al 2006; Dick and MacCall 2011). This method assumes that, as part of a closed population, animal migration does not occur outside the study site and is therefore well suited to scallops (Kangas et al 2011). Depletion estimation has been used to estimate abundance and catch efficiency in Australian, Canadian, Isle of Man and US scallop fisheries (Beukers-Stewart et al 2001; Walter et al 2007; Kangas et al 2011; Smith and Hubley 2013). Linear depletion estimators, such as the Leslie and Davis (1939) method, assume that the probability of capture of all individuals is uniform, the catch is proportional to sampling effort and that the catch at any point is dependent on the prior cumulative catch (Rago et al 2006). However, these assumptions are often violated by the limited movement of semi-sedentary organisms, such as king scallops, which cannot be assumed to re-mix within the study area after each haul and do not have either random or uniform spatial distributions (Rago et al 2006; Hennen et al 2012). Therefore, depletion estimators applied to these types of species must be spatially explicit and record exactly which parts of the study area were sampled during each haul (Hennen et al 2012).

Other methods exist to estimate catch efficiency, e.g. using optical methods or dives pre- or post-dredging (Caddy 1968; 1971; Beukers-Stewart et al 2001; Fifas et al 2004; Lambert et al 2014; Miller et al 2019), mark-recapture (Dickie 1955) and dredging over known abundance on seeded grounds (McLoughlin et al 1991). Many of these methods are often preferred because they require considerably less sampling effort than depletion estimation, which requires large sampling effort to provide enough information to the mathematical estimators (Beukers-Stewart et al 2001). However, depletion estimation may be preferred over other methodologies because either it is not restricted to shallow waters or can be conducted at the spatial scale of the fishery (Beukers-Stewart et al 2001).

In Wales king scallop populations are currently managed using input controls such as gear and effort restrictions (The Scallop Fishing (Wales) (No. 2) Order 2010, Table 1.8), however none of these are based on a stock assessment. Quantification of the absolute catch efficiencies of commercial vessels targeting king scallops could allow for the conversion of catch rates to abundance remaining on the seabed in the dredge tracks. This could allow commercial vessels with known catch efficiency to perform industry-based stock assessment surveys designed to directly estimate abundance, which are not currently conducted in the fishery. However, as it is unlikely that the catch efficiency of each vessel in the fishery could be quantified it is important to understand the variation in catch efficiencies if industry-based stock assessment surveys were to be used to estimate abundance directly for this fishery.

The focus of this study was to quantify the variation in catch efficiencies in commercial scallop dredgers and explore the effects of vessel characteristics, individual vessel fishing practices and sediment type on the estimated catch efficiencies. Additionally, the initial density and local abundance of commercially sized scallops in each lane was estimated. This was achieved via a large-scale depletion experiment involving five commercial fishing vessels, conducted as part of a larger experiment designed to quantify the impact of scallop dredging on benthos (Lambert et al 2017). The study area was a closed scallop ground of approximately 110 km^2 within the Cardigan Bay Special Area of Conservation (SAC), which has been closed to commercial scallop dredging since June 2009 (Sciberras et al 2013). This area provided an ideal setting for conducting this study as it had accumulated a high abundance of king scallops, as estimated by research surveys conducted in the area since 2012 using Newhaven dredges (Lambert et al 2014; Delargy et al 2019).

2.2 Materials and Methods

Depletion Experiment

A large-scale fishing impact experiment was conducted in April 2014 and consisted of five commercial scallop dredgers fishing 13 equally sized rectangular lanes (Lambert et al 2017). Each lane was 1700 m long and 370 m wide and had two turning areas at each end so that vessels could fish in straight lines through the fishing lanes. Four additional, randomly selected lanes were unfished and acted as control lanes while the 13 fished lanes were fished at different intensities (Figure 2.1). The fishing intensity of each lane was the ratio of cumulative effort (swept area) to the area of a lane. An intensity of one meant that the cumulative effort applied to a lane was equal to the area of the lane.

Multiple (four to 120) hauls were conducted within fishing lanes. Global Positioning System (GPS) devices on board each vessel recorded latitude and longitude position at between one to 10 minute intervals (most commonly one minute intervals) to ensure they fished within the lanes and to accurately track haul paths. A haul was recorded from when the dredges reached the seafloor to the moment they were hauled. Hauls where the majority of the haul path had fallen outside of a fishing lane were excluded from the analysis. The GPS data were used to determine the fishing intensity on a fine spatial scale within each lane. These spatial data were also used to estimate the length of hauls and vessel speed during each haul. This information was used for analysis of variation in estimated catch efficiencies, and haul length was also used to estimate swept area.

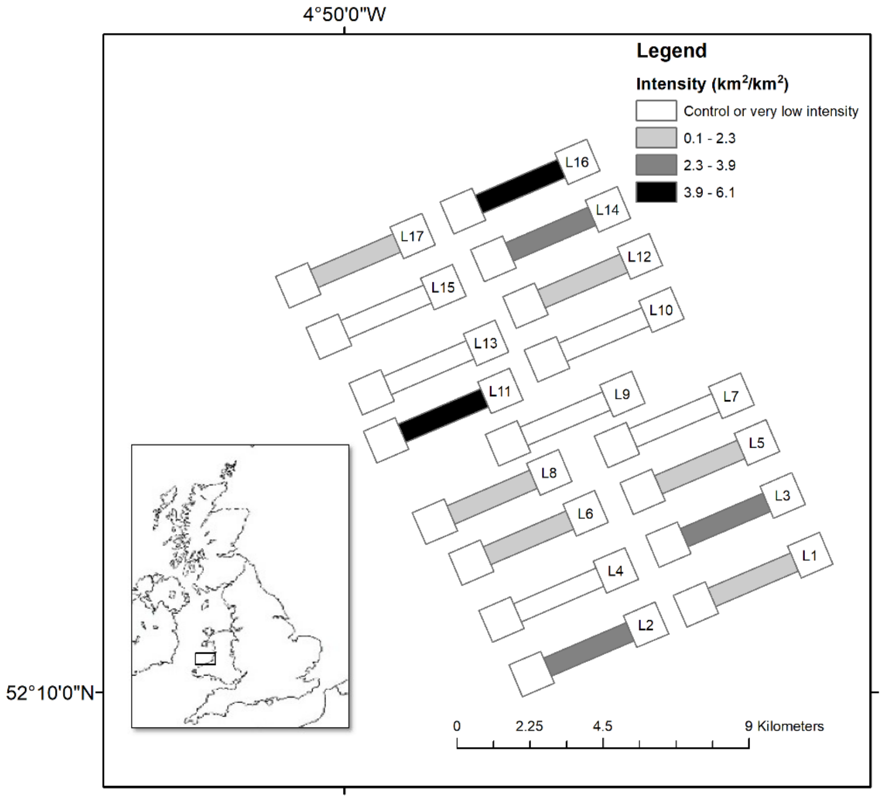


Figure 2.1: A map of the lanes sampled during the fishing intensity experiment conducted in Cardigan Bay in 2014. Lanes are shaded according to fishing intensity (km^2/km^2), ranging from white (control or very low intensity) to black (high intensity). The lane name is displayed for each fishing lane. The black rectangle in the inset map indicates the position of the fishing lanes in the United Kingdom.

No two vessels fished the same lane but each vessel fished up to four lanes (Table 2.1). Each vessel varied in length, weight, engine capacity and number of dredges towed. The vessels towed spring-loaded Newhaven dredges, each of 76cm width, and in two evenly numbered gangs from each side of the vessel. The distance between the two sets of dredges perpendicular to the direction of the haul was determined for each vessel based on skipper knowledge (Table 2.1), and these distances were used to estimate the position of each gang of dredges relative to the position of the vessel during hauls. The sampling was designed to ascertain the relationship between the depletion of benthic biota with fishing intensity (Lambert et al 2017) and was not originally intended to be used to estimate catch efficiency or scallop abundance. Nevertheless, the dataset provided a unique opportunity to investigate variation in multiple vessel's catch efficiencies over a small spatial scale.

The catch of scallops was recorded as number of bags of scallops per haul. Typical bag weight was 28 – 35 kg, depending on the vessel, and included shell weight and only scallops ≥ the minimum landing size (MLS) of 110 mm in shell width. Scallop catch was not recorded as precise weight or abundance, nor were scallops less than the MLS recorded, as high catch volume prevented time-consuming counts and precise weight measurements, and observers were not present on every vessel through the entirety of the experiment. Estimating landings from approximate bag weights has the potential to introduce variation and small sources of bias. However, bag weights were crosschecked with the landed weight of scallops at seafood processors which purchased the scallops from this experiment to validate the consistency of vessel bag weights. Individual scallop weight was obtained from subsamples of approximately 45 individuals from each haul where an observer was present. Observers were present on a subset of hauls across the experimental design, and all scallops in the subsamples were ≥ the MLS. Individual weight was used to convert from catch weight to abundance.

Table 2.1: The number of fishing lanes fished by each vessel and the characteristics of each vessel from the fishing intensity experiment.

Vessel	Number of lanes fished	Number of dredges towed	Distance between gangs of dredges (m)	Length of vessel (m)	Gross registered tonnage	Engine power (kW)
Vessel 1	2	6	1	11.4	10	107
Vessel 2	2	8	14	12.0	29	220
Vessel 3	2	8	9	13.4	36	221
Vessel 4	3	14	0	15.0	59	214
Vessel 5	4	14	6.5	27.2	99	221

Each lane was sampled by 15 to 27 0.1 m^2 Hamon grabs during a survey conducted prior to the depletion fishing in March 2014 and another survey conducted in September 2014, as described by Lambert et al (2017). Grabs were randomly spread throughout each lane. From each grab, 40 g of sediment was categorised on the Folk (1954) scale after particle size analysis (Lambert et al 2017). As the mud content was relatively constant among samples, the gravel to sand ratio was calculated for each fishing lane. The gravel to sand ratio was not incorporated in the depletion estimator, but was used to address whether sediment type could explain variation in the estimated catch efficiencies.

Data preparation

The number of bags of scallops per haul were converted to catch weight (kg), using the typical bag weight for each vessel. Catches, expressed as number caught ≥ MLS per haul, were obtained by dividing scallop catch weight (≥ MLS) by mean individual weight (≥ MLS). Mean individual weight was specific for each lane and obtained from observer subsamples.

Three fishing lanes (L8, L10 and L15) were excluded from further analysis as less than 45 % of the lanes were swept, which likely violated the depletion estimation assumption that a substantial proportion of the initial abundance was removed by fishing. In these three fishing lanes, there was also limited overlap of hauls such that sufficient depletion did not occur (Hennen et al 2012). This resulted in only one lane for Vessel 2 and only two lanes for Vessel 5 remaining in this analysis (Table 2.1). A small number of the remaining hauls (eight of 585 hauls, ~1.4%) were removed from the analysis. Hauls were removed because either no GPS positions were recorded (three hauls from L12), or catch data were missing (five hauls from L3).

A 'hit matrix' was estimated for each fishing lane, as outlined by Rago et al (2006) and Hennen et al (2012), to accurately record the overlap of hauls. This was required as the fishing patterns were not systematic and scallop distribution could not be considered random, as the animals are semi-sedentary, and failure to account for these would bias the resultant catch efficiency and initial density estimates by the patterns which the vessels fished each lane (Rago et al 2006; Hennen et al 2012). We used the method from Hennen et al (2012) to estimate the hit matrix, which recorded the number of times a grid of evenly spaced positions (10 cm apart, less than the MLS of king scallops in Wales) were swept by the dredges. This method avoided the need to consider grid cell size in the Rago et al (2006) hit matrix method. This Hennen et al (2012) method applied here assumed no indirect effect of fishing on positions not directly contacted by the gear, which is a common assumption of depletion estimators.

To record the number of times each position was swept by the dredges in each lane, the dredge path between two observed GPS positions was estimated as two rectangles, one corresponding to each gang of dredges. Each vessel was assumed to travel in a straight line between GPS positions, and the rectangles were configured to the angle of the haul between the positions to reflect the direction of travel of the dredges. The width of each rectangle (dimension which was perpendicular to the haul direction) was the number of dredges in that gang (half the total number of dredges) multiplied by the width of a single dredge (76 cm). The length of each rectangle (dimension which was parallel to the haul direction) was calculated as the straight-line distance between the two observed dredge GPS positions. Each rectangle was offset from the observed GPS position so that the inner edge (the edge closest to the vessel) was half the distance between the two gangs of dredges (Table 2.1) away from each vessel , to better reflect each gang's likely position on the seabed. Each set of rectangles represented a segment of a haul and the 10 cm grid positions which fell within each set of rectangles were incremented by one to indicate those positions had been swept once more. The final hit matrix was the number of positions on the grid swept j times before and during each haul, and from this the fraction of each haul which had been swept j number of times at the conclusion of the haul was also estimated. Each fraction included times swept prior to and during the haul.

The area of the rectangles were added together to obtain the swept area of each segment and the swept area and length of each haul were calculated as the sum of the swept area and sum of lengths of the segments within each haul, respectively. Catch-per-unit-effort (CPUE) was calculated as the number of ≥ MLS scallops caught divided by the swept area, by haul. The speed of the vessel in each segment was calculated from the length of segment and the known time between GPS positions, and then the mean vessel speed was estimated for each haul. The percentage of area in each lane which was fished at least once and the fishing intensity applied to each lane were estimated from the estimated swept areas and, along with haul speed and haul duration, served as descriptive statistics, but were not used in the depletion estimator.

Depletion estimator

The hit matrix, fraction of each haul swept j times, catches (number of ≥ MLS king scallops per haul), CPUE, length of haul and total width of gear were used as observed data for the Patch model developed by Rago et al (2006) to estimate the catch efficiency of the vessel fishing each lane and the initial density ≥ MLS king scallops in each lane. The Patch model, as with any statistical depletion estimator, estimates CPUE for each haul based on removals by previous hauls (Hennen et al 2012). However, unlike other depletion estimators, the Patch model also considers the fractions of each haul previously fished j times when estimating CPUE. For example, a haul which largely falls in a previously unfished part of a study area (in this case an individual fishing lane) would result in a higher estimated CPUE than a haul which largely falls overly previously fished parts of the study area (Hennen et al 2012). Other depletion estimators, such as the Leslie and Davis (1939) method, expect CPUE to continually decline with order of hauls, which would be an inappropriate assumption of the sampling conducted in the present study. Estimated CPUE per haul (i) in the Patch model was therefore the product of the effective swept area (a) and the initial density (D_0) (Eq 2.1), as also described by Rago et al (2006) and Hennen et al (2012).

$$CPUE_i = a_i * D_0 \tag{2.1}$$

The initial density was a parameter estimated by the model, and the effective swept area was defined by the catch efficiency (e) and the fraction of each haul hit j times (f) (Eq 2.2), as written in Hennen et al (2012). The Hennen et al (2012) hit matrix method employed here removes the cell width parameter in Hennen et al (2012) from Eq 2.2. The catch efficiency was an estimated parameter.

$$a_i = ea_i \sum_{j=1}^{i} f_{i,j}(1-e)^{j-1} \tag{2.2}$$

Observed catches were assumed to follow a negative binomial distribution (Eq 2.3) in the Patch model with mean equal to the estimated catches and variance defined with a dispersion parameter (k) (Eq 2.4). Catches were converted between CPUE and absolute catches using the observed length of hauls and total width of the gear.

$$C_i^{obs} = Negative\ Binomial(C_i^{est}, \delta_i^2) \tag{2.3}$$

$$\delta_i^2 = C_i^{est} + \frac{(C_i^{est})^2}{k} \tag{2.4}$$

The negative binomial distribution is commonly used for modelling benthic invertebrate catches as it for can accommodate many zeros and a wide range of values (Hennen et al 2012). The negative log-likelihood of the model was minimised by automatic differentiation to estimate k and the two other unknown parameters, e and D_0 (Eq 2.5). The Patch model version used was written in Automatic Differentiation Model Builder (ADMB) which supports the application of automatic differentiation. For each fishing lane, the estimated initial abundance and 95% confidence intervals was obtained by multiplying the estimated D_0, and the respective 95% confidence intervals, by the area of the fishing lane.

$$-LL(k, D_0, e|C_i, a_i) = k\sum_{i=1}^{l}\left(\ln\left(1+\frac{D_0 a_i}{k}\right)\right) + \sum_{i=1}^{l} C_i\left(\ln\left(\frac{D_0 a_i}{D_0 a_i + k}\right)\right) \tag{2.5}$$

The Patch model was used here because it is suitable for semi-sedentary species and is also suitable when depletion fishing patterns are not systematic (Rago et al 2006; Hennen et al 2012), as was the case in the present study. Furthermore, the Patch model has been shown to provide robust estimates of catch efficiency and initial density under a wide range of scenarios and the sensitively and reliability of these estimates are well understood after extensive testing by Hennen et al (2012) and Wilberg et al (2013).

2.3 Results

A total of 577 hauls over 10 lanes were analysed. The highest catch rate observed from a single haul was 25.2 scallops ≥ MLS per 100 m^2 (L5, sixth haul) and the lowest catch rate observed from a single haul was 0.4 per 100 m^2 (L14, 43rd haul). The fishing intensity achieved across these 10 fishing lanes ranged from relatively low (1.1 $km^2 km^{-2}$) up to in excess of what may be expected from a commercial fleet (6.1 km^2km^{-2}) (Table 2.2). The fishing effort in each of the lanes was reasonably well spread, but did not cover all the seabed in each lane and areas of the fishing lanes were swept varying number of times (Appendix Figure 1). Accordingly, the percentage of fished seabed in each lane ranged from 65.4 % to 98.7 % (Table 2.2). The amount of time taken to fish each lane from start to end varied, and ranged from 3.4 to 27.3 days (Table 2.2). The gravel content (fraction of gravel from the gravel to sand ratio) of fishing lanes ranged from 0.07 to 0.88 (Table 2.2) (Lambert et al 2017).

Table 2.2: The intensity, percentage fished, estimated catch efficiency, gravel content, number of days used to fish lanes and estimated king scallop abundance and density of each fishing lane from the fishing intensity experiment and Patch model.

Lane	Vessel	Catch efficiency (fraction of ≥ MLS scallops caught in haul path)	Average intensity achieved (km^2km^{-2})	Percentage of lane fished (%)	Average gravel content (fraction of gravel from gravel + sand)	Estimated king scallop (≥ MLS) abundance in lane	King scallop (≥ MLS) density (abund./100m^2)	Duration of time between start and end of fishing the lane (days)
L1	Vessel 1	0.35	1.1	65.4	0.81	266533	42.4	23.0
L5	Vessel 1	0.62	1.6	77.0	0.68	186160	29.6	27.3
L3	Vessel 2	0.32	3.8	97.5	0.33	214463	34.1	16.3
L2	Vessel 3	0.47	3.0	90.0	0.88	175671	27.9	6.8
L6	Vessel 3	0.51	1.2	70.5	0.53	160707	25.5	3.4
L12	Vessel 4	0.47	2.3	87.6	0.07	156820	24.9	7.7
L16	Vessel 4	0.35	6.1	98.2	0.50	371649	59.1	15.0
L17	Vessel 4	0.26	1.9	85.4	0.32	298276	47.4	4.6
L11	Vessel 5	0.13	5.3	98.7	0.08	215783	34.3	8.5
L14	Vessel 5	< 0.0001	3.9	97.2	0.79	NA	NA	17.8

Fished areas of seabed within the lanes were swept between one to 25 times (25 times swept occurred in areas of L16) (Figure 2.2). The pattern of depletion, defined as overlap of hauls, with haul order also varied, with one vessel choosing to sample small areas within a lane repeatedly (indicated by a high number of sweeps in areas in early hauls) and then moving to unfished parts of the lane (Vessel 4 in L12, L16 and L17) (Figure 2.2). The other lanes, and consequently the other vessels, had low fractions of seabed swept multiple times in early hauls and higher fractions of seabed swept multiple times in later hauls, indicating these vessels had largely sampled unfished sections of these lanes initially before then generating depletion patterns by sampling fished areas in later hauls.

The estimated catch efficiency for L14 was unrealistically low (< 0.0001) (Table 2.2). Hennen et al (2012) showed that vessels with low catch efficiency may not provide enough information to the Patch model to appropriately estimate catch efficiency and initial density, as low efficiency results in smaller initial catches which makes it challenging for the model to distinguish between depletion patterns and noise in catches. L14 was fished by Vessel 5, which also fished L11. The estimated catch efficiency for L11 was the lowest of the remaining (and realistic) estimated catch efficiencies (Table 2.2), indicating that Vessel 5 had low catch efficiency. The reason a realistic catch efficiency was estimated for L11 and not L14 is likely due to greater depletion patterns in the hauls compared to L14 (Figure 2.2). As a consequence of the unrealistically low estimated catch efficiency, L14 was not considered further in this study.

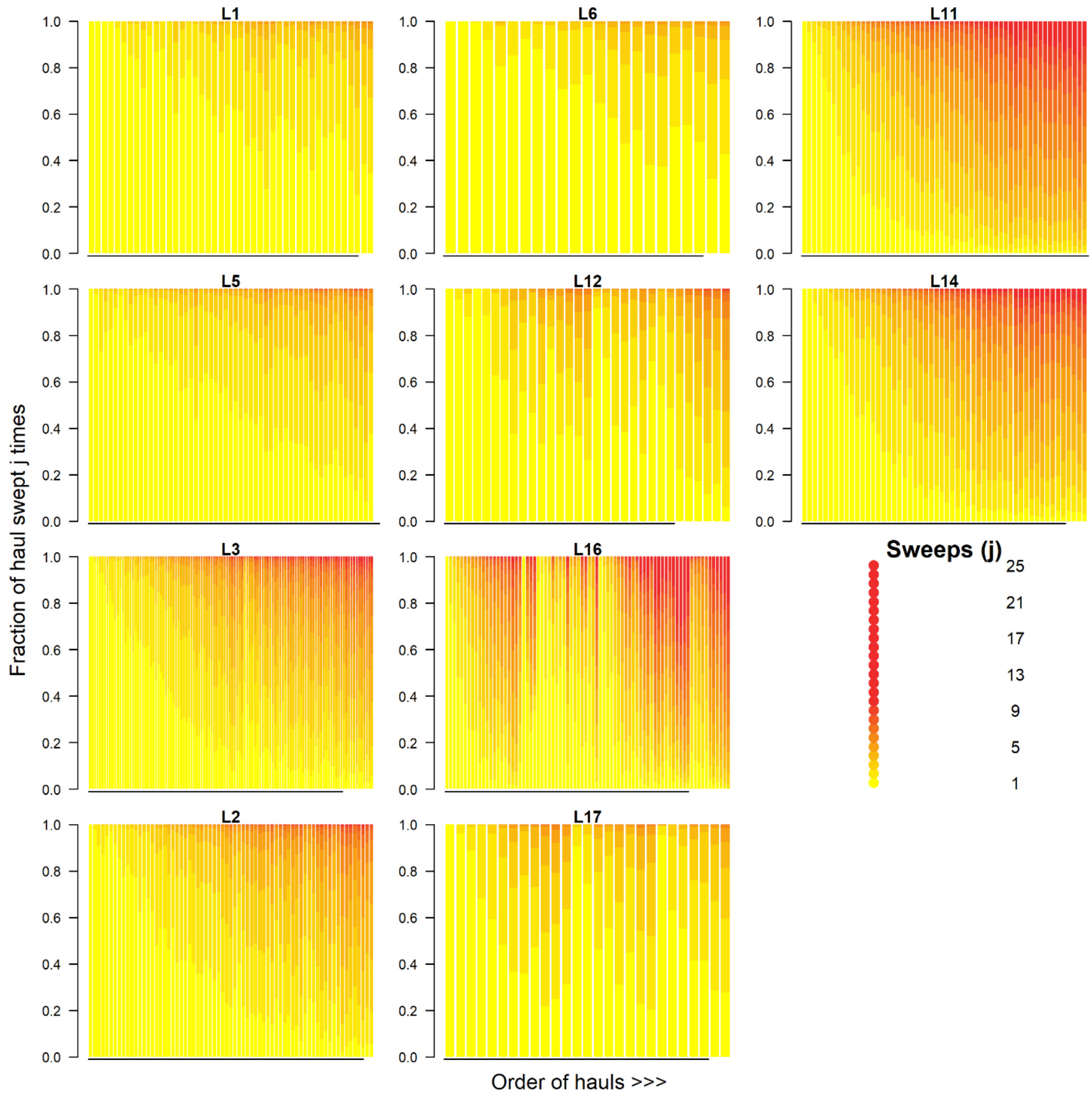


Figure 2.2: The area sampled during each haul, grouped by fractions representing the number of times areas were swept j number of times. This includes the number of times the area was swept during previous hauls and the number of times the area was swept during the current haul. Each panel corresponds to a fishing lane and in each the x-axis is the chronological order of hauls. The y-axis in each panel is the fraction of the haul which was swept j times, and each column sums to one. The fractions are coloured by number of times swept (sweeps) as indicated in the figure legend.

Plots of standardised residuals indicating the difference between estimated and observed catches per haul were inspected for the nine remaining lanes to assess whether the model estimated catches were sensible (Appendix Figure 2). These residuals indicated several of the lanes had an unusually high amount of observed catches which were less than the estimated catches, which is important when considering the reliability of the estimates from the model as discussed later. The estimated catch efficiency of scallops ≥ MLS ranged from 0.13 to 0.62 between lanes (Table 2.2). Three vessels had multiple catch efficiency estimates, as they fished two or three lanes which produced realistic catch efficiency estimates. Vessel 3's catch efficiency estimates were similar (0.47 and 0.51), however Vessel 4 produced three estimates which were more different (0.26, 0.35 and 0.47) and Vessel 1 produced two considerably different estimates (0.35 and 0.62). There was variation in confidence around these estimates between vessels (Figure 2.3). The 95%

confidence intervals around the efficiency estimates for Vessels 1, 3 and 4 were wider than the other two vessels, and the difference between the lower and upper 95% confidence intervals was 0.2 or higher in some cases. In contrast, the 95% confidence interval range around the efficiency estimates for Vessels 2 and 5 were less than 0.05.

Catch efficiency was lowest for the longest and heaviest vessel (Vessel 5) (Figure 2.4). This vessel also towed the (joint) most dredges (7 a-side). The mean fishing practices of each vessel, such as length, duration, speed and swept area of hauls differed (Figure 2.5). The vessel with the lowest catch efficiency, Vessel 5, hauled for the longest distances, durations, at the highest speeds and consequently swept the most area per haul on average. This variation between vessels existed as this experimental design was not initially designed for depletion analysis. Gravel content in the sediment could not help explain the variation in catch efficiencies as vessels did not sample a wide range of sediment types (Figure 2.6).

Abundance estimates for the fishing lanes (0.629 km^2) ranged from 156,820 to 371,649 king scallops ≥ MLS (Table 2.2). This corresponds with densities of 24.9 to 59.1 per $100m^2$. The 95% confidence intervals of these estimates were highly variable between fishing lanes (Figure 2.3). In multiple lanes the difference in density between the upper and lower 95% confidence intervals was less than 15 scallops ≥ MLS per 100 m^2, however in others lanes there were differences in density of approximately 20, 40, 60 and 100 king scallops ≥ MLS per 100 m^2 between the upper and lower 95% confidence intervals. There was no pattern between gravel content of the sediment and estimated initial density (Figure 2.6).

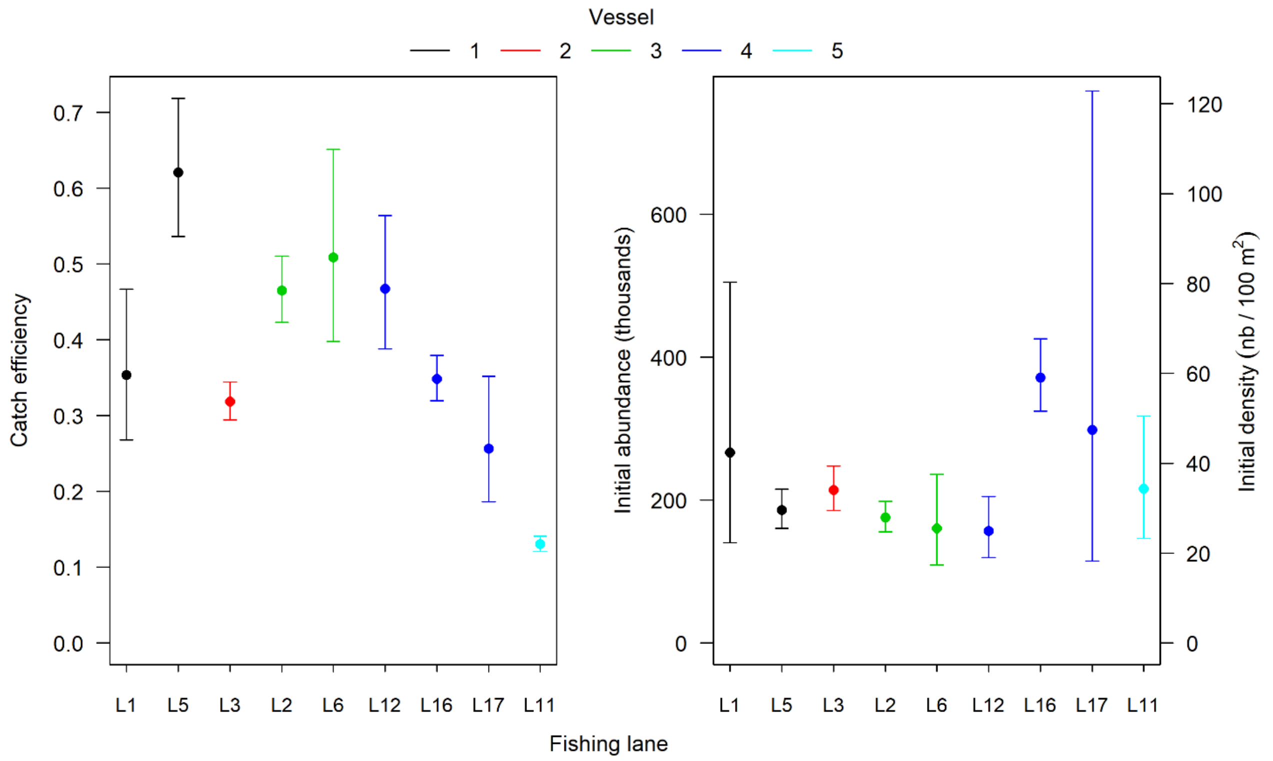


Figure 2.3: Catch efficiency (left) and initial density (right) for each fishing lane estimated by the Patch model. Both panels display the model point estimate for each lane, along with 95% confidence intervals. Both panels are presented by fishing lane and coloured by vessel as indicated in the figure legend. Two y-axes are provided in the right-hand panel, which correspond to the same points and confidence intervals. These are the estimated initial abundance in each fishing lane, expressed as thousands of king scallops ≥ MLS, and estimated initial density, expressed as each abundance divided by the area of each fishing lane (in 100 m^2).

2.4 Discussion

The results show that catch efficiency differed considerably among vessels, and that estimates of catch efficiency for the same vessel differed between lanes. This underlines the need to better understand catch efficiency for commercial vessels if they are to be used in a fishery-independent stock survey which randomly samples the entire geographic range of the Welsh king scallop stock(s). The variation in catch rates observed between lanes were a magnitude higher than the variation observed in the abundance estimates between lanes. This indicates that observed differences in catch rates between vessels do not necessarily reflect fluctuations in abundance. This is important as using perceived changes in abundance, caused by unaccounted for changes in catch rates, may trigger inappropriate management decisions if commercial vessels were to be used for stock assessment in the future.

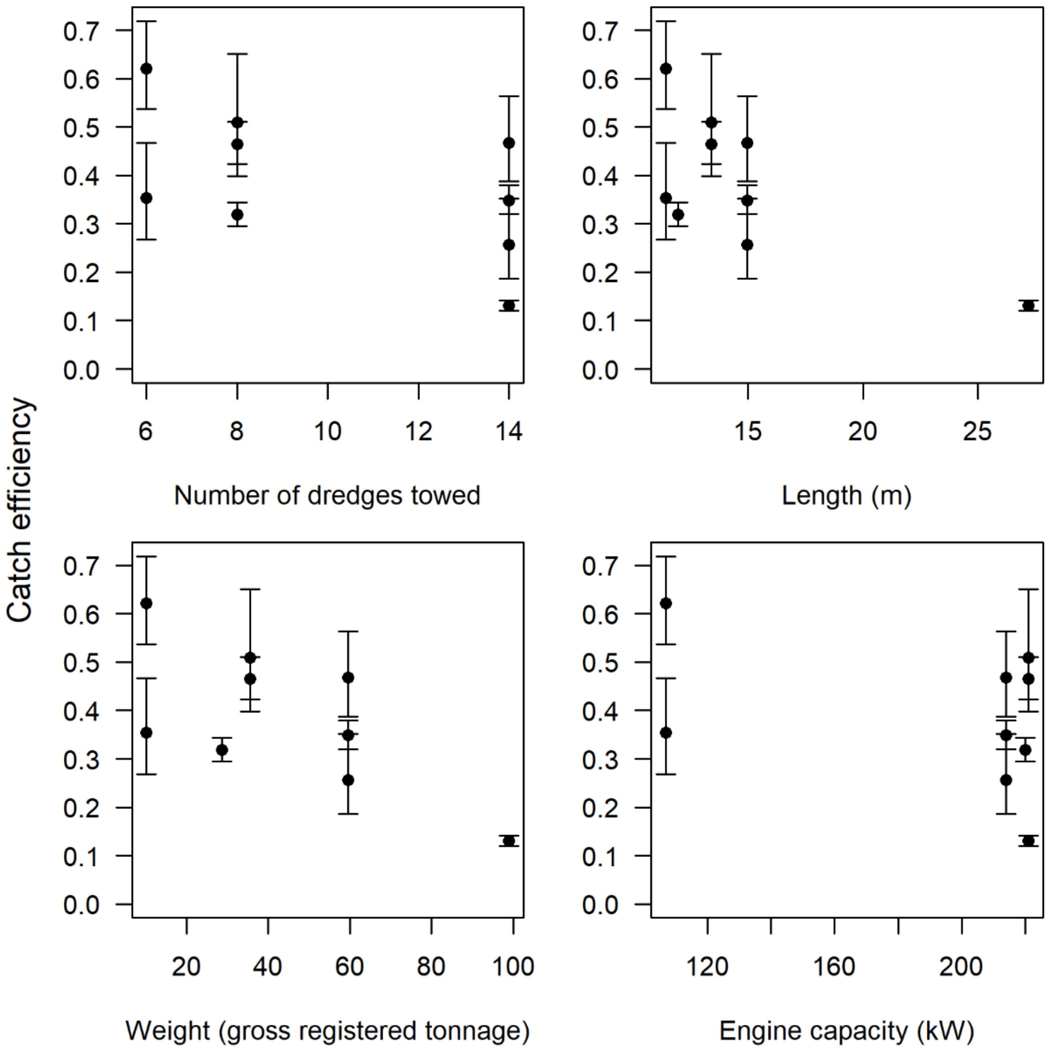


Figure 2.4: Four characteristics of the vessels from the fishing intensity experiment plotted against estimated catch efficiency and respective 95% confidence intervals. Top left: the number of dredges towed by each vessel. Top right: the length of each vessel (m). Bottom left: the weight of each vessel (gross registered tonnage). Bottom right: the engine capacity of each vessel (kW).

Three of the nine catch efficiencies estimated in this study were within the range estimated by Beukers-Stewart et al (2001) (0.295 to 0.407), for king scallops ≥ 110 mm in shell width and estimated by divers and depletion estimation. The lower five catch efficiencies estimated here were within the range reported for other king scallop fisheries that used similar Newhaven spring-loaded dredges (0.06 to 0.41), however these estimates were either the catch efficiency of all sizes of king scallops (Chapman et al 1977; Lambert et al 2014) or for those above a different MLS (90 mm shell width, Dare et al 1993). The upper four catch efficiencies here were higher than this range. All the catch efficiencies estimated here were within the broader range of estimates for towed gears targeting a range of scallop species (0.02 to 0.81) (Caddy 1968; NEFSC 2001), of which the full range have been obtained using a variety of methods including divers (e.g. Caddy 1968; Beukers-Stewart et al 2001), mark recapture (e.g. Gruffydd 1972), depletion (e.g. NEFSC 2001; Walter et al 2007), seeded grounds (e.g. McLoughlin et al 1991) and optical methods (e.g. Miller et al 2019). The catch efficiency estimates from the present study are also within the observed catch efficiency range of other towed fishing gears, such as beam or otter trawls (< 0.05 to > 0.94) (Joll and Penn 1990; Munro and Somerton 2002; Somerton et al 2007).

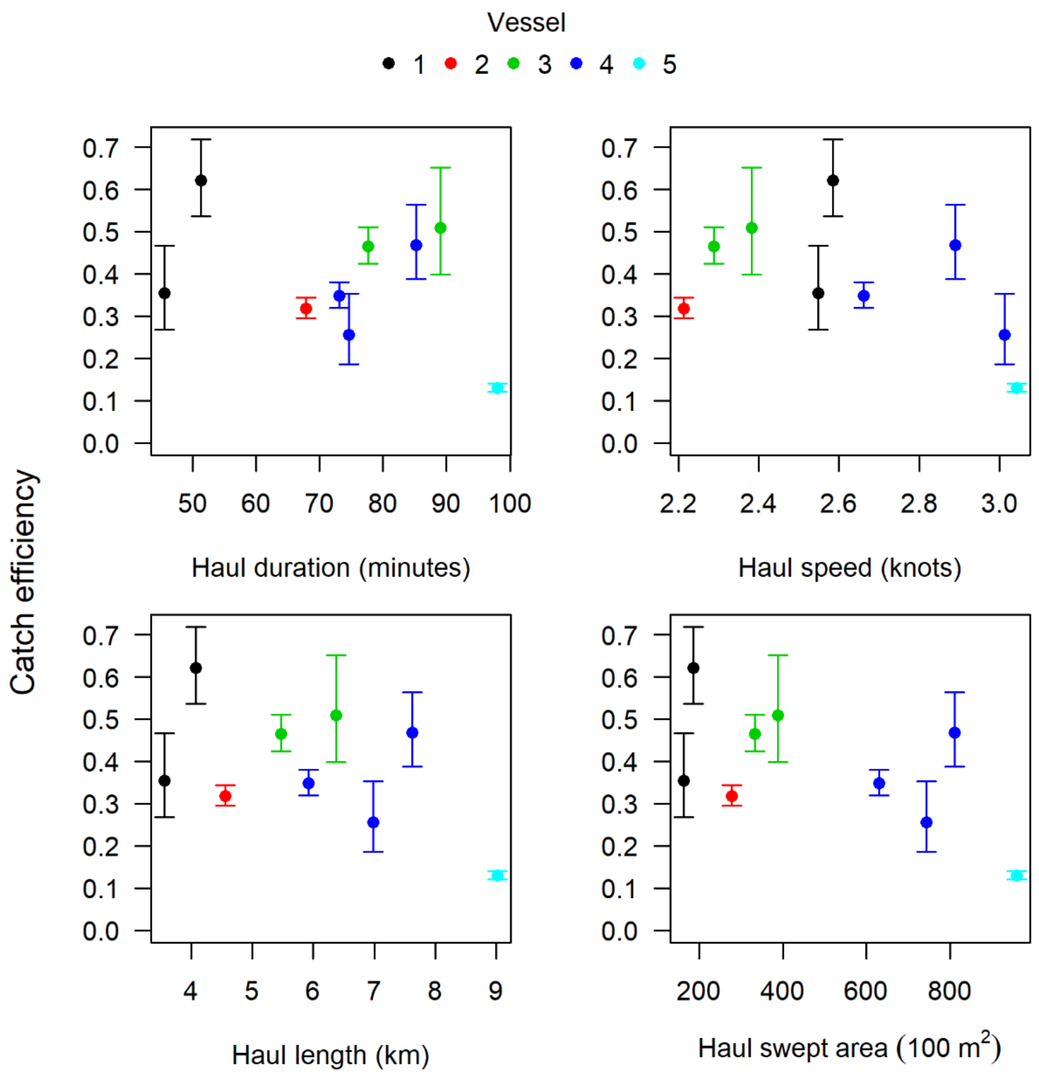


Figure 2.5: The mean fishing practices employed in each fishing lane from the fishing intensity experiment plotted against estimated catch efficiency and 95% confidence intervals. Top left: the mean haul duration (minutes). Top right: the mean haul speed (knots). Bottom left: the mean haul length (km). Bottom right: the mean swept area (100 m^2). Each point is coloured by vessel as indicated in the figure legend.

In the present study, the largest vessel, measured by length and weight, had the lowest catch efficiency. Often it is expected that a larger, heavier vessel may have greater catch efficiency than smaller, lighter vessels as the heavier vessels are less affected by roll and pitch reducing contact time of the gear with the seabed (Byrne et al 1981). However, we argue that this vessel was underpowered relative to its size, as there is a restriction on engine capacity for scallop vessels in Welsh waters of 221 kW (Table 1.8), and this may explain this vessel's low catch efficiency. The relatively low engine capacity of this vessel may have limited its ability to maintain desired speed in the strong tides found in Cardigan Bay (Fifas et al 2004). The speed of the vessel affects both the contact time of the gear with the seabed and the mouth opening of the gear, and consequently affects catch efficiency (Carrothers 1981; Fifas et al 2004; Reiss et al 2006). On average, this vessel fished at the highest speeds of any of the five vessels in the experiment and this may have been a consequence of being unable to maintain a desired speed. On average, this vessel also fished the longest hauls, by time and length, and swept the most area per haul, which may also partly explain the lower catch efficiency. Longer hauls leading to a greater swept area can result in a net or dredge becoming full, or the opening becoming blocked, before the end of the haul and this will result in reduced catch efficiency if the gear was unable to catch further target species (Shafee 1979; Zhang et al 1993). Interestingly, there was no evidence that the number of dredges hauled had an effect on catch efficiency from the present study. In addition, sediment type could not help address the variation in catch efficiencies as the effect of sediment type could not be separated from the effect of individual vessel as vessels did not sample a wide range of sediment types.

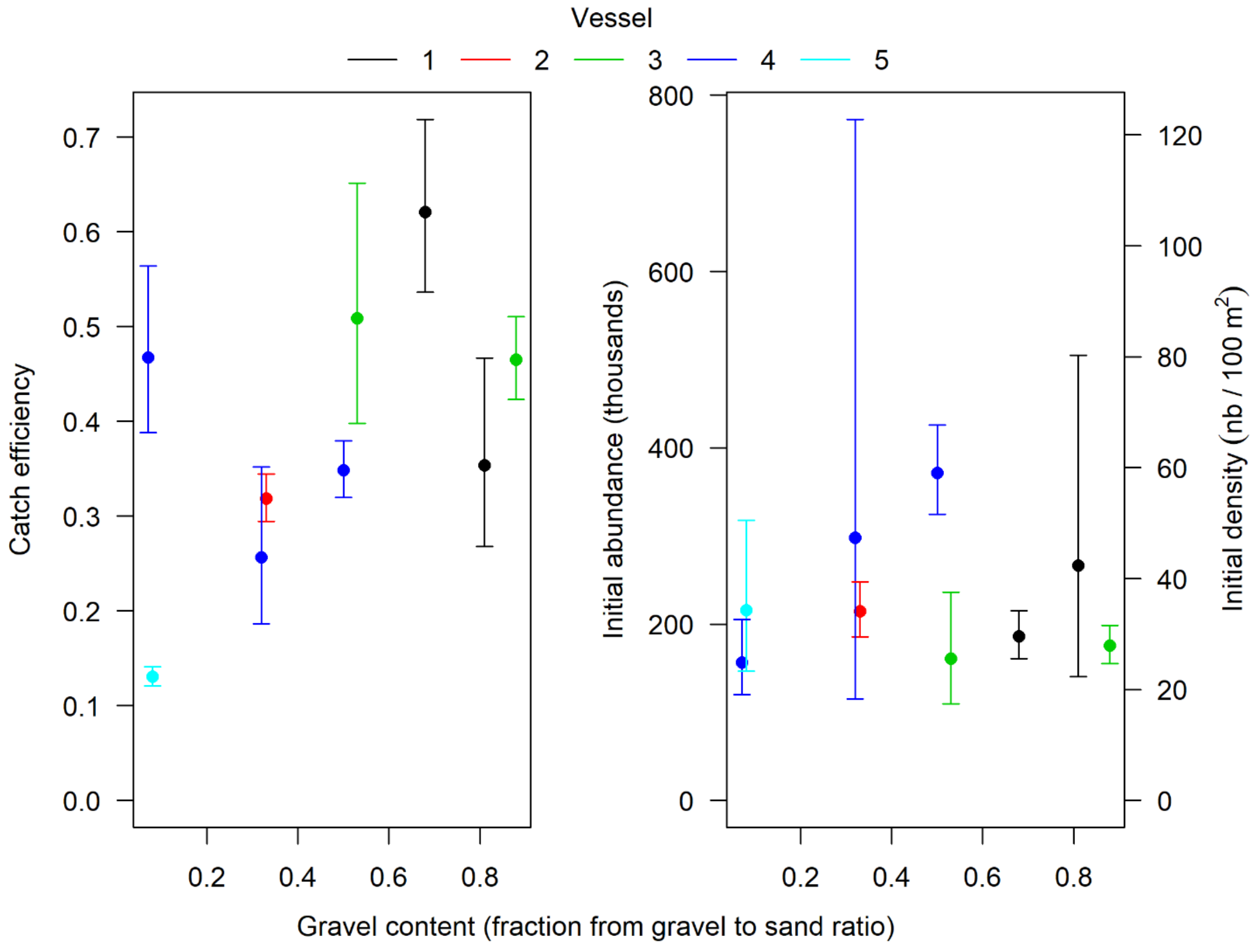


Figure 2.6: Patch model estimated catch efficiency (left) and initial density (right) plotted against the fraction of gravel from the amount of sand and gravel in each fishing lane. Vessels are coloured as indicated in the figure legend. Both panels display the model point estimate for each lane, along with 95% confidence intervals. Two y-axes are provided in the right-hand panel, which correspond to the same points and confidence intervals. These are the estimated initial abundance in each fishing lane, expressed as thousands of king scallops ≥ MLS, and estimated initial density, expressed as each abundance divided by the area of each fishing lane (in 100 m^2).

Some of the remaining variation in vessel catch efficiency may be explained by technical differences in the dredges between vessels (Fifas et al 2004). Technical gear data were not available, but the technical gear characteristics were strictly defined for vessels fishing in Welsh waters (Table 1.8). All vessels used in this study were operating at the maximum permitted number of teeth, spacing of teeth and starting chainmail bag ring size, and therefore we assume little variation in these aspects between vessels. Other potential sources of variation in the gear could include wear of teeth or chainmail bag rings (Lart 2003). Differences in the operation of the gear, such as warp length, spring compression and handling, and vessel-specific practices, including turning, hauling and shooting, may also have contributed towards the observed variation in catch efficiencies (Carrothers 1981). Variation in these factors remain unquantified in our study, and we assumed they remained constant for each vessel throughout the duration of the experiment as a unique crew operated each vessel.

Variation in estimates may have also been caused by accuracy of GPS positions, hit matrix or Patch model. The Hennen et al (2012) hit matrix implemented here reduces error in efficiency estimates and reduces the inter-quantile range of both efficiency and density estimates in comparison to the Rago et al (2006) hit matrix method (Hennen et al 2012). However, the hit matrix method implemented here increases error in density estimates in comparison to the Rago et al (2006) method. Therefore, more confidence should be placed in the efficiency estimates than the density estimates in the present study. Catch efficiency estimates from the Patch model are considered fairly robust and perform well against other depletion estimators, apart from situations of considerable positional error (Hennen et al 2012; Wilberg et al 2013). Errors in positional data used to generate the hit matrices can result in a 20 % underestimation of density and increased error in positional data results in increased error in efficiency estimates (Hennen et al 2012; Wilberg et al 2013). However, it is impossible to quantify the exact impact on Patch model estimates from errors in positional data (Hennen et al 2012).

In the present study, GPS positions were recorded from each vessel, and skipper knowledge was used to determine the likely distance between each gang of dredges and each vessel. However, the skippers noted that the positions of the dredges relative to the vessel were controlled by a variety of factors including the direction and strength of the tide, which is not accounted for in our analysis. Therefore, the positional data used here will be imprecise on the 10 cm spatial scale used in the hit matrix estimation and consequently these Patch model estimates should be treated with some caution. This may also help explain why catches were overestimated in some lanes by the model (as highlighted by residual plots), if in fact the vessels in these lanes were fishing over previously fished ground more than the positional data indicated. Future studies wishing to implement this model should consider GPS devices on the dredge bar of each gang of dredges to obtain a more accurate position of the dredges (Hennen et al 2012). Patch model estimates are also affected by the densities and patchiness of target organisms within study sites, as individual hauls can easily hit or narrowly miss highly dense aggregations (Hennen et al 2012). However, the exact effect of patchiness on the estimates in this present study are not quantifiable and future studies should consider the use of divers or optical methods to examine depletion study sites prior to sampling (Hennen et al 2012).

Vessels with a lower catch efficiency result in less accurate Patch model estimates because they catch less per unit effort and therefore provide less information to the model when sampling an unfished area (Hennen et al 2012). Furthermore, low efficiency vessels make it harder for the model to detect a depletion signal from noise in the catches (Hennen et al 2012). Therefore, all other things equal, the Patch model estimates for the highest efficiency vessels should be most reliable in the present study. Importantly, the effect of low catch efficiency can be accounted for with greater sampling effort and a greater overlap of hauls within a depletion experiment (Hennen et al 2012). Increased overlap in hauls may explain why the Patch model produced realistic estimates for L11 but failed to produce realistic estimates for L14, as these lanes were fished by the same vessel which had estimated low efficiency.

In the future catch efficiency may be understood and quantified by a wide range of alternative techniques, including divers (e.g. Beukers-Stewart et al 2001), mark recapture (e.g. Gruffydd 1972), index removal (e.g. Gedamke et al 2005) seeded grounds (e.g. McLoughlin et al 1991) and optical methods (e.g. Miller et al 2019). Alternatively, optical methods can be used to directly sample scallop stocks and sidestep the need to estimate catch efficiency of towed gears altogether. Capture efficiency (equivalent of catch efficiency) of optical methods can be close to one, which is considerably better than most towed gears, and this can result in more accurate estimates of abundance (Stokesbury 2002). Absolute abundance of sea scallops has been routinely estimated using optical methods in the US, with the absolute abundance of the total survey area estimated using the mean density of sea scallops from video samples taken across small areas (Stokesbury 2002; Stokesbury et al 2004). This camera system is now able to measure shell height of the scallops, detect greater numbers of juvenile sea scallops, and the absolute abundance estimation accounts for both the selectivity and capture efficiency of the method (Carey and Stokesbury 2011; Bethoney and Stokesbury 2018).

Table 2.3: Densities of king scallop from closed areas reported in other studies

Region	Closed area	Maximum density (abundance/100 m^2)	Assessment Method	Size classes	Sampling period (inclusive)	Year area closed	Reference
Isle of Man	Brada Inshore	20	Divers	All sizes	1989 - 2003	1989	Beukers-Stewart et al 2005
English Channel	Various areas in Lyme Bay	40	Video	All sizes	2007 and 2016	2006	Hinz et al 2011; Kaiser et al 2018
Wales	Cardigan Bay SAC	85	Still image camera	All sizes	2009 - 2011	2009	Sciberras et al 2013
Wales	Cardigan Bay SAC	21	Video	All sizes	2012 - 2014	2009	Lambert et al 2014
Wales	Cardigan Bay SAC	59.1	Depletion estimation	≥ 110 mm shell width	2014	2009	This study
Scotland	Lamlash Bay Marine Reserve	5	Divers	≥ 100 mm shell width	2010 - 2013	2008	Howarth et al 2015
Scotland	Lamlash Bay Marine Reserve	1	Divers	< 100 mm shell width	2010 - 2013	2008	Howarth et al 2015
Scotland	Lamlash Bay Marine Reserve	5.1	Still image camera	> 50 mm shell width	2009 – 2014	2008	Boulcott et al 2018

The densities estimated in the present study were within the range of king scallop densities from other closed areas (1 – 85 per 100 m^2), although not to the same size category as the present study (Table 2.3). Lambert et al (2014) also sampled the present study site in 2014 using a video camera towed from a research vessel and the reported densities (21 per 100 m^2) were lower than any estimated in the present study. Lambert et al (2014) reported densities for all sizes of king scallops, and therefore this estimate should be higher than those estimated here. Differences in densities could be due to natural fluctuations or the accuracy of the two different techniques used (videos and depletion estimation).

Although the specifications of Newhaven dredges are designed with a MLS in mind, they are likely to catch a considerable amount of under MLS scallops (Lart 2003). Therefore, our density estimates would be even higher if we had data on under MLS scallops caught during the experiment. Regardless, our study highlights that king scallop densities vary considerably over a relatively small area. Both the difference in density estimates from other studies and the broad range estimated here reinforce the need for annual surveys to assess fluctuations in abundance over time and across small spatial scales.

This study has shown that there is considerable variation in the catch efficiency of individual vessels targeting king scallops with dredges, and estimates from the same vessel can vary over small spatial scales. This indicates further understanding is required before commercial vessels should be considered for stock assessment surveys. The catch efficiencies estimated here are also directly useful as prior distributions for stock assessment modelling or future studies to help improve understanding of catch efficiency in other scallop fisheries. Using knowledge of catch efficiency, and how this varies by vessel, to adjust catch rates is important for such fisheries, as otherwise large variations in catch rates may be linked with variations in abundance which have not occurred. Abundance can then be under- or overestimated. Estimates of abundance typically drive management decisions for fisheries and it is important that these decisions be based on the most accurate abundance estimates possible. This study has also shown scallop densities, and consequently abundances, vary considerably over small spatial scales, indicating that detailed scientific surveys continue to be required to accurately assess scallop stock status.

CHAPTER 3: HOW MEASURES OF DREDGING EFFICIENCY CHANGE WITH REPEATED FISHING OF AN AREA

Abstract

Bottom trawling and dredging are the greatest cause of anthropogenic disturbance to the world's seabed habitats. However not all fisheries, fleets, or vessels will have the same impact. The level of impact varies with the vulnerability of the benthic fauna on the fishing ground, which reflects a combination of species characteristics, abundance, gear characteristics and amount of contact of the gear with the seabed. To enable an evaluation of trade-offs between vessel profitability and the environmental impacts of fishing, it is important to have an understanding of fuel and environmental efficiency per unit of target species landed. We investigated how environmental and fuel efficiency changed as scallop dredgers repeatedly fished areas of the seabed in an experimental setting, and whether either of these measures of efficiency could help address the trade-off between continuing to fish an area or to target another area. Environmental efficiency was quantified as change in relative benthic status (RBS) per tonne of king scallops (*Pecten maximus*) landed. We expected that if a vessel's ability to catch scallops (catch efficiency) was higher than the impact on benthos caused by their gear (benthic depletion rate), then the change in RBS per tonne of king scallops landed would increase with increasing cumulative effort, i.e. the environmental impact increases relative to the catches as fishing continues in an area. We show this with simulations, and the empirical evidence from the experiment supported this expectation. The fuel efficiency of three of the vessels was also quantified throughout the experiment as fuel intensity (litres of fuel used to land a tonne of catch). We expected fuel intensity to increase with increasing cumulative effort, as more fuel is required to catch a tonne of scallops when local populations are depleted. We show this with simulations, and the empirical evidence from all vessels supported this expectation. These analyses indicated that highly efficient vessels should lightly fish areas, whereas less efficient vessels expend more effort to areas. This work has also demonstrated how fuel intensity changes as areas are repeatedly fished. These findings provide support for management strategies that account for economic and environmental viability of seabed fisheries and attempt to balance trade-offs and maximise efficiency across multiple objectives.

3.1 Introduction

Bottom trawling and dredging for commercially harvestable marine species is the single greatest direct cause of anthropogenic disturbance to the world's seabed habitats (Kaiser et al 2002; Amoroso et al 2018). The impacts of these fishing methods include damage to the physical environment and reductions in epifaunal and infaunal biomass and diversity (Sciberras et al 2018) and the development of conservation and ecosystem-based management approaches requires assessment of these impacts (Pikitch et al 2004; Rice 2013; Hiddink et al 2017). These approaches make use of a variety of tools available to managers such as marine protected areas and gear modifications, the latter designed to reduce friction with the seabed or let unwanted catch escape (Campbell and Cornwell 2008; Planes et al 2009; Jenkins and Garrison 2013). One way to reduce the negative impacts, while maintaining fisheries landings, is to better understand or improve the efficiency of these fishing gears.

Fishing efficiency can be measured in a variety of ways, including the proportion of target species caught per unit of effort (catch efficiency) (Itaya et al 2007), the quantity of unwanted bycatch per unit of effort (Steele et al 2002), the changes that occur to the seabed habitat per unit effort (Sowunmi et al 2016), by economic factors such as fuel consumption per unit effort (Suuronen et al 2012) or a combination of these metrics (Jacobsen et al 2017). Different stakeholders such as fishers, managers or conservationists, will have different priorities for which metric to adopt to evaluate gear efficiency. For most fishers, this is likely to be an economic priority where maximising profit, which is likely to be positively related to catch rate, becomes the objective (Hilborn and Walters 1992). For conservationists, it is likely to be an environmental priority where minimising impacts on the ecosystem is the primary goal. Ideally, all could be evaluated against each other in the context of an ecosystem approach.

Although a fishers' primary objective may not be necessarily to maximise their economic efficiency, it is important to be economically efficient to remain viable (Hilborn and Walters 1992). The vessels in many fisheries are likely to target areas of high catch rates that are relatively close to their home port (Hilborn and Walters 1992; Beukers-Stewart et al 2003; Shepperson et al 2016). The decision about when to move on from an area as local biomass is being depleted is complex, and is likely to be dependent on a number of factors. These include (un)certainty on the catches in the currently fished and alternative areas, the cost of travelling to a new fishing ground, distance of the new ground to home port and weather conditions (Hilborn and Walters 1992). One commonly used, simple metric to describe a vessel's or fishery's fuel efficiency is fuel intensity, which is the fuel use per unit of catch landed (often expressed as litres per tonne) (Driscoll and Tyedmers 2010; Parker and Tyedmers 2015). Fuel intensity is known to be influenced by a variety of factors such as the gear, vessel size and engine capacity and trip length (Driscoll and Tyedmers 2010). This metric may be used to describe how fishers decide when to move on as a fishing ground becomes depleted, as they will be aiming to maintain high catches relative to fuel consumption (therefore low values of fuel intensity). However, the decision to stop fishing a patch of the sea solely based on fuel intensity may not necessarily lead to environmental efficiency.

Environmental efficiency of demersal fishing gears, fisheries or vessels can be quantified through the change in the status of the benthic invertebrates living on the seabed caused by each unit of catch landed. This state of the seabed community can be estimated using the relative benthic status (RBS) method, which describes the change in biomass of benthic communities using a logistic population growth model (Schaefer 1954) which has been extended to incorporate fishing impacts (e.g. Hiddink et al 2017; Pitcher et al 2017). The change in RBS caused by each fishing haul is particularly useful, as this can be standardised relative to the landings. Using this metric, the best environmental fishing efficiency would result in minimising the negative change in RBS per unit (of catch) landed [ΔRBS-PUL]. Both fuel intensity and ΔRBS-PUL can be important efficiency metrics when vessels repeatedly fish an area. Sessile benthic species, such as king scallop (*Pecten maximus*), which move less than 30 m over a period of 18 months (Howell and Fraser 1984), are likely to remain in an area even when it is fished multiple times. Therefore catch rates are likely to decrease as fishing continues, resulting in an increase in fuel intensity and a decrease in ΔRBS-PUL, i.e. a more negative, and greater environmental impact.

One way of managing repeated fishing of a semi-sedentary target species within a defined area is to use rotational management. Rotational management may take a variety of forms, but often involves dividing the fishing ground in to a number of areas that are alternatively closed and opened over a defined period of time. The objectives of such an approach are usually to let sections of the seabed recover between fishing events and protect juveniles whilst fishing continues in other areas (Little et al 2015; Stewart and Howarth 2016). Rotational management, based on catch rates, may be very effective for scallop fisheries, where the vessels often tend to fish an area repeatedly until the catch rate decreases below economically viable levels, and then move on to another patch (Beukers-Stewart et al 2003; Tindall et al 2016). Rotational management has been implemented in a number of scallop fisheries around the world (Hart and

Rago 2006; Flood et al 2014; Williams et al 2014). Rotational management can also be implemented in real-time. This involves closing areas of the fishery when a catch rate threshold, or limit, is exceeded. It is a technique emerging in both the US and Europe (Little et al 2015). One example is in the Shetland king scallop fishery where areas are closed when the LPUE drop below a pre-defined threshold (Tindall et al 2016). A trade-off between fuel intensity, catch rates and ΔRBS-PUL could be used to determine an effort limit which could be assigned to areas in real-time rotational management. This could allow for recovery of the seabed, for protection of juveniles and ensure economic efficiency. A suitable trade-off analysis may be Pareto efficiency, which is a measure of the collective efficiency of multiple objectives, and is defined as the point where it is impossible to improve the efficiency of a single objective without reducing the efficiency of another (Jacobsen et al 2017). Pareto efficiency can be quantified through efficiency frontier frameworks, a technique which uses a series of equations to calculate efficiency (Jacobsen et al 2017).

In the UK king scallops are typically targeted using Newhaven dredges, and in Wales are currently managed using input controls such as gear and effort restrictions and minimum landings sizes (MLS) (The Scallop Fishing (Wales) (No. 2) Order 2010, Table 1.8). The Cardigan Bay Special Area of Conservation (SAC) has been closed to commercial scallop dredging since June 2009 (Sciberras et al 2013). Some areas of the SAC have since amassed relatively high king scallop densities (mean of approximately 8 caught per 100m^2 swept), as estimated by research survey Newhaven dredges in 2013 (Lambert et al 2014). Simultaneously, landings have continued to decrease around Wales since 2012 (Figure 1.4) (MMO 2016; 2018) and implementing rotational management could be considered for the Welsh king scallop fishery to be able to effectively harvest the king scallop population whilst minimising seabed habitat impacts.

The focus of this study was to examine if ΔRBS-PUL and fuel intensity changed with cumulative fishing effort as we expected when areas were repeatedly fished. We focused our study on the semi-sessile king scallop. To demonstrate the expected relationship of ΔRBS-PUL and fuel intensity with increasing effort we conducted simulations, and supplemented these with empirical values estimated from an experimental setting. In addition, we also display RBS values based on empirical fishing effort to illustrate the change in RBS as fishing continued. The empirical data was obtained from a large-scale depletion experiment involving multiple commercial fishing vessels, conducted as part of a larger experiment designed to quantify the impact of scallop dredging on the benthos (Lambert et al 2017).

3.2 Materials and Methods

Depletion Experiment

A large-scale fishing impact experiment was conducted in April 2014 in an area of approximately 110 km^2 in the Cardigan Bay SAC, as described in Chapter 2. The entirety of this area had been closed to commercial scallop dredging since June 2009 (Sciberras et al 2013). The experiment consisted of five commercial scallop dredgers fishing 13 equally sized rectangular lanes (Lambert et al 2017). The fuel consumption of the five vessels was not recorded during the experiment, but typical daily fuel consumption levels were obtained for three of the vessels after the experiment had taken place. All skippers were contacted by telephone, but only three of the skippers responded. The sampling was designed to ascertain the relationship between the depletion of benthic biota and fishing intensity (Lambert et al 2017) and was not originally intended to be used to estimate RBS or fuel intensity. Nevertheless, the dataset provided a unique opportunity to investigate the ΔRBS-PUL and change in fuel intensity whilst vessels repeatedly fished the same areas.

Change in RBS per unit of king scallop landed (ΔRBS-PUL) simulations

To illustrate how we expected ΔRBS-PUL to change with increasing cumulative effort, we conducted simulations under a variety of scenarios. Here, we demonstrate how ΔRBS-PUL was affected by the relationship of the depletion rate of benthic invertebrate biomass per unit of fishing effort (*D*) and the absolute catch efficiency of the fishing vessel (*q*). Vessel catch efficiency will affect the landings, which will result in a smaller ΔRBS-PUL for a more efficient vessel applying the same effort as a less efficient vessel. The depletion rate of the gear on the benthos affects the change in RBS, and a greater change in RBS will lead to a greater ΔRBS-PUL. Therefore, the relationship between *q* and *D* is important because this will determine the resultant impact on the benthos relative to the amount of target species caught. This is an important consideration when conceptualising the efficiency of fishing in relation to environmental impacts associated with that fishing activity.

The simulated change in RBS (ΔB) of the seabed community over time was described using a logistic growth equation (Schaefer 1954), modified to account for depletion caused by fishing effort (Eq 3.1). *B* was RBS, *R* the recovery rate of the benthic invertebrate biomass, *K* the carrying capacity of the benthic invertebrate biomass in an area, *D* the depletion rate of the benthic invertebrate biomass and *F* the effort ratio of swept area relative to the size of an area. This approach has been implemented in multiple recent works to estimate RBS (e.g. Smith et al 2007; Ellis et al 2014; Hiddink at al 2017; Pitcher et al 2017), as it can be simply applied to data whilst providing an effective portrayal of the recovery rate of benthic biomass (Hiddink et al 2017). Here, a time step was a single haul (*h*). In our empirical data, all hauls were conducted within a month and it was assumed that no recovery of the benthic invertebrate community occurred between successive hauls. Therefore, in our simulations the recovery rate of the seabed community between hauls (*R*) was assumed to be effectively 0, which simplified Eq 3.1 to Eq 3.2.

$$\Delta B_h = RB_h\left(1 - \frac{B_h}{K}\right) - DF_hB_h \tag{3.1}$$

$$\Delta B_h = -DF_hB_h \tag{3.2}$$

Simulated initial RBS ($B_{h=1}$) was assumed to be 1, as the depletion experiment area had not been commercially fished since closure in June 2009 (Sciberras et al 2013). The simulated swept-area ratio (*F*) was set to 0.05 for each simulated haul, as this was similar to the swept area ratios from the depletion experiment. Simulated RBS (B_h) was updated after each haul (Eq 3.3).

$$B_{h+1} = B_h + \Delta B_h \tag{3.3}$$

The equation for calculating change in RBS can also be described by Eq 3.4.

$$\Delta B_h = -DF_hB_{h=1} \times \prod_{i=1}^{h-1}(1 - DF_{h=i}) \tag{3.4}$$

Simulated ΔRBS-PUL was then calculated by dividing simulated ΔB by the simulated scallop king scallop landing per haul (tonnes). Simulated scallop landings per haul (L_h) for each lane were estimated using *q, F* and a simulated king scallop population (*N*) (Eq 3.5). The initial king scallop population ($N_{h=1}$) was set to 100 (units could be numbers or biomass), and the population was updated after each haul assuming no population growth or natural mortality occurred between hauls (Eq 3.6).

$$L_h = qF_hN_h \tag{3.5}$$

$$N_{h+1} = N_h - L_h \tag{3.6}$$

Simulated ΔB was then divided by simulated L for each haul. Each simulation was conducted for 200 timesteps (hauls). A simulation was conducted for each combination of four depletion rates (0.1, 0.2, 0.3 and 0.4) and four absolute catch efficiencies (0.1, 0.2, 0.3 and 0.4), resulting in 16 simulations.

Fuel intensity simulations

To illustrate how fuel intensity was expected to change with increasing cumulative effort, and therefore a decreasing king scallop population, we conducted simulations under a variety of scenarios. Simulated fuel intensity (l/tonne of scallops) was calculated as the fuel consumption divided by simulated king scallops landed from each haul. The simulated population and the landings were calculated using Eq 3.5 and Eq 3.6. The initial king scallop population ($N_{h=1}$) was set to 2000 (units could be numbers or biomass). This population was larger than that used in the ΔRBS-PUL simulations for graphical purposes and so that the simulated fuel intensities were on a scale similar to values of fuel intensity from other studies (e.g. Driscoll and Tyedmers 2010). Each simulation was conducted for 200 timesteps (hauls). A simulation was conducted for each combination of four fuel consumption rates (250 l, 500 l, 750 l and 1000 l) and four absolute catchabilities (0.1, 0.2, 0.3 and 0.4), resulting in 16 simulations.

Estimation of empirical ΔRBS-PUL and fuel intensity

To verify our simulations, we calculated empirical ΔRBS-PUL using the calculations described for the simulations. Firstly, we did this using two different depletion rates which were best estimates of the actual depletion rate. The first depletion rate was 0.2, as estimated from global meta-analysis of dredges by Hiddink et al (2017). The second depletion rate was 0.105, which was the mean of the two biomass depletion rates between March and May 2014 for two groups of invertebrates (D = 0.12 infauna, D = 0.09 epifauna) estimated by Lambert et al (2017) from the fishing intensity experiment which the empirical data in the present study were obtained.

All hauls were conducted within a month, and it was assumed that no recovery of the benthic community occurred between successive hauls. Initial RBS in each fishing lane at the start of the experiment ($B_{h=1}$) was assumed to be 1, as the area had not been commercially fished since closure in June 2009 (Sciberras et al 2013). Scallop dredging effort (F) of each haul was expressed as the ratio of swept area of each haul to the effective area of each fishing lane. The effective area of each fishing lane was the actual area of the fishing lane minus the areas which were not swept at all within each lane, as including areas that were not impacted would underestimate ΔRBS-PUL. ΔRBS-PUL was estimated by dividing the empirical change in RBS per haul by the observed landings from that haul (live weight (includes shell), tonnes of king scallops).

Empirical fuel intensity (l/tonne of scallops landed) was calculated as the fuel consumption divided by the observed landings of each haul. Fuel intensity was only calculated for the fishing lanes which were fished by the three vessels which had reported a daily fuel consumption rate (seven fishing lanes). Vessel trip fuel consumption (l) was estimated as the product of daily fuel consumption values and the length of each trip in days, where a trip was defined as the between leaving port and returning to port. Fuel consumption for each trip was spread among hauls based on the amount of swept area relative to the other hauls on that trip. This method assumed that fuel consumption was directly related to area swept, but in reality was likely to vary with multiple factors including speed and direction of tide and sea state. However, as these data were not recorded during the experiment the approach described here was deemed the most appropriate. Although this method did not assign the true fuel consumption to each haul, it did ensure that the steaming distance of each trip was accounted for and spread evenly across hauls.

Statistical analyses

For purely illustrative purposes, the empirical estimates of each of RBS, ΔRBS-PUL and fuel intensity were presented against cumulative effort (swept area, cumulative by individual fishing lane) (*cA*) alongside curves from a linear mixed effects model fitted to the relationship between the metric (y_i) and cumulative effort across all data (or for only data corresponding to three vessels in the case of fuel intensity). In addition, vessel (*v*) was incorporated as a random covariate, fishing lane (*L*) as a fixed covariate and ε represented remaining residual variation in each model. Each relationship was described by a quadratic polynomial (Eq 3.7), and the parameters ($\beta 1_i, \beta 2_i, \beta 3_i$) estimated using R (R Core Team 2019) and the saemix package (Comets et al 2017). This package was chosen because it provided the individual parameter estimates as a function of the individual random effects, the covariate matrix and the fixed effects. Simpler or more complex variations of the model were not considered as, for all metrics, the model adequately accounted for non-independence in individual data points and the estimated curves were satisfactory fits to the empirical data.

$$y_i = \beta 1_i + \beta 2_i (cA * v * L) + \beta 3_i (cA * v * L)^2 + \varepsilon_i \tag{3.7}$$

3.3 Results

The fishing effort in each of the lanes was reasonably well spread, but did not cover all the seabed in each lane (Appendix Figure 1). As a consequence, the effective area swept at least once in each fishing lane was less than the true area of the fishing lanes (Table 3.1). Fishing lane L16 was fished in thirds and consequently effort was not spread homogenously in this lane, and therefore L16 was analysed in thirds. Fishing lanes L8, L10 and L15 were excluded from the analyses as less than 45 % of the lanes were fished, which reduced the chance of hauls passing over each other. This was important for the analysis, as if the hauls did not pass over each other, then the estimated empirical RBS would be lower than reality as hauls passing over each other were required deplete the benthos. The length, speed, duration and swept area of individual hauls varied within and between vessels (Figure 2.5). Vessels also differed in the number of days they took to fish a lane and the total number of trips made during the duration of the experiment (Table 3.1). The change in king scallop catch rates with increasing cumulative effort for each of the fishing lanes displayed depletion patterns, and were discussed in Chapter 2.

Table 3.1: The number of trips conducted by each vessel during the fishing intensity experiment, the percentage of each lane that was fished, the resultant effective area and the duration of time between starting and ending the fishing of each lane.

Vessel	Number of trips made during experiment	Fishing Lane	Percentage of lane fished (%)	Effective area ($100m^2$)	Duration of time between starting and ending the fishing of the lane (days)
Vessel 1	17	L1	65.4	4113.66	23.0
		L5	77.0	4843.30	27.3
Vessel 2	11	L3	97.5	6132.75	16.3
Vessel 3	4	L2	90.0	5661.00	6.8
		L6	70.5	4434.45	3.4
Vessel 4	8	L12	87.6	5510.04	7.7
		L16a	98.2 (for all L16)	2058.93	7.0
		L16b	98.2 (for all L16)	2058.93	15.0
		L16c	98.2 (for all L16)	2058.93	14.8
		L17	85.4	5371.66	4.6
Vessel 5	3	L11	98.7	6208.23	8.5
		L14	97.2	6113.88	17.8

Relative Benthic Status

The equations used to estimate RBS from empirical fishing effort data (Eq 3.2 and Eq 3.3) resulted in an initial, linear rapid decline in estimated RBS when D = 0.2, and then a slowing of decline with increased cumulative effort (Figure 3.1). The rate of decrease was dependent on the amount of effort applied in each haul relative to the size of the effective area of each fishing lane The amount of effort applied in each haul relative to the size of the effective area differs with vessel based on the size of effective area and both the number of dredges towed and chosen haul length. When D = 0.105, the gradient of the decreasing line was shallower with increasing cumulative effort (Figure 3.1). Estimated empirical change in RBS is not explicitly presented, yet this information is incorporated in Figure 3.1.

ΔRBS-PUL

The simulations of ΔRBS-PUL demonstrated that ΔRBS-PUL decreased with increased cumulative effort when the depletion rate (*D*) was less than the vessel absolute catch efficiency (*q*). It remained constant when these two values were equal, and increased when *D* was greater than *q* (Figure 3.2). Additionally, the rate of increase or decrease was greater when the difference between *D* and *q* was greater.

The estimated empirical ΔRBS-PUL displayed a variety of relationships with increasing cumulative effort for each of the vessels, which reflected the slopes from Figure 3.1 corrected for decreasing landings with increasing cumulative effort and the depletion rate used in the calculations (Figure 3.3). ΔRBS-PUL initially increased for both Vessels 1 and 5 with increasing cumulative effort for both depletion rates, but then ΔRBS-PUL decreased with increasing cumulative effort (Figure 3.3). The change from increase to decrease in ΔRBS-PUL occurred after considerably different amounts of cumulative swept areas for these vessels and depletion rates. The opposite pattern was true for both Vessels 2 and 4, where ΔRBS-PUL initially decreased with increasing cumulative effort for both depletion rates, but then ΔRBS-PUL increased with increasing cumulative effort (Figure 3.3). Again, the change, in this case from decrease to increase in ΔRBS-PUL, occurred after considerably different amounts of cumulative swept areas for these vessels and depletion rates. ΔRBS-PUL always decreased with increased cumulative swept area, and for both depletion rates, for Vessel 3 (Figure 3.3). However, the rate of decrease increased with increasing cumulative effort.

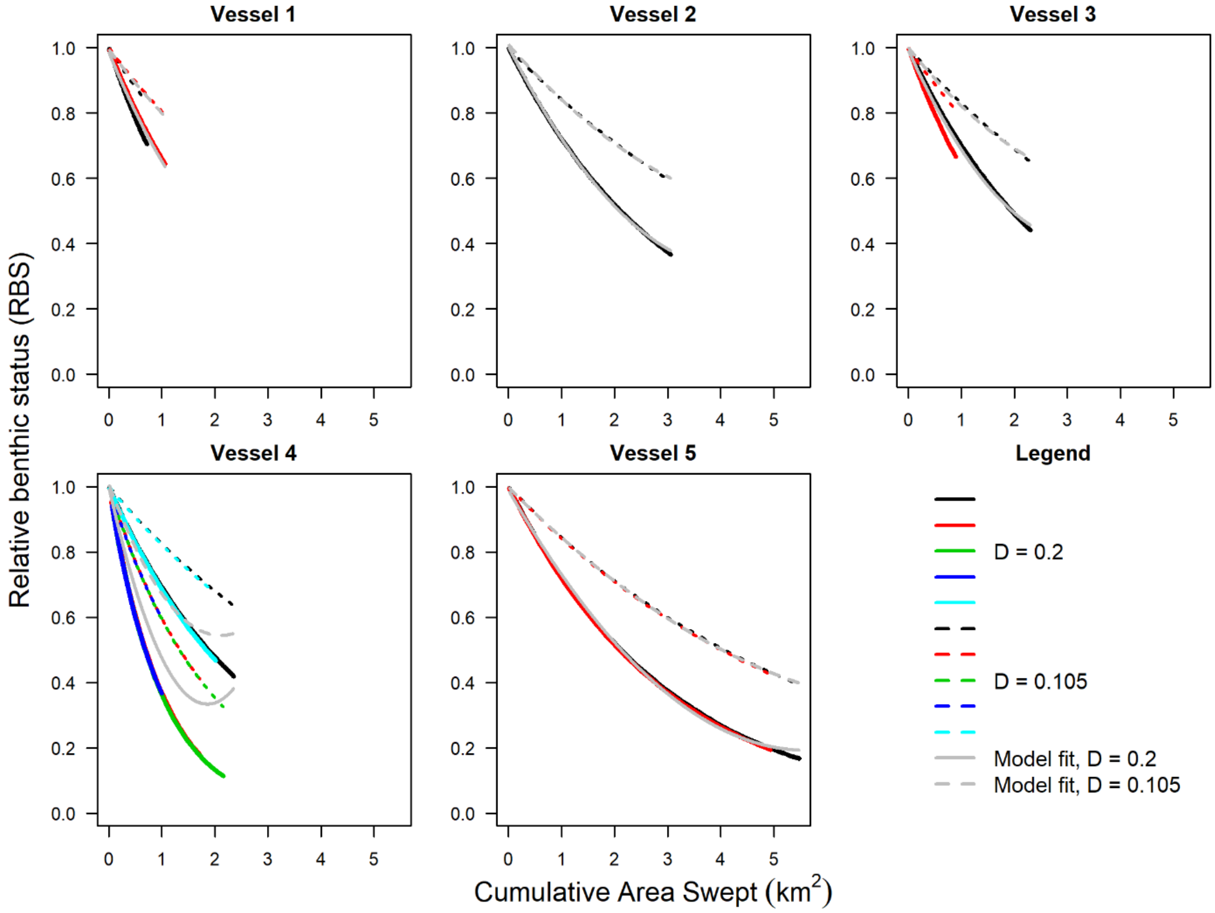


Figure 3.1: Estimated empirical RBS plotted against cumulative effort (swept area (km^2)) for individual hauls and separated by vessel, from the fishing intensity experiment. Cumulative effort is cumulative by fishing lane, and consequently each coloured line (black, red, green, blue and turquoise) correspond to an individual fishing lane. Unbroken lines for each fishing lane were estimated using depletion rate D = 0.2, and broken lines were estimated using D = 0.105. Grey lines are statistical model fits applied to all lanes fished by each vessel, and the unbroken grey line on each panel is the fit when D = 0.2 and the unbroken when D = 0.105.

Fuel intensity

The simulations of fuel intensity showed that a higher vessel catch efficiency led to a more rapid increase in fuel intensity with increasing cumulative effort (Figure 3.4). A higher fuel consumption rate also led to a more rapid increase in fuel intensity with increasing cumulative effort (Figure 3.4). Empirical fuel intensity increased gradually with increasing cumulative effort for both Vessels 1 and 4 (Figure 3.5). Fuel intensity increased more rapidly with increasing cumulative effort for Vessel 3, which led to a curve with a positive gradient (Figure 3.5). Fuel intensities ranged from 67 to 439 l/tonne for Vessel 1, 92 to 1772 l/tonne for Vessel 3 and 22 to 632 l/tonne for Vessel 4.

3.4 Discussion

Estimated RBS

Estimated empirical RBS decreased with increasing cumulative effort, as expected when no recovery was assumed. Differences in the rate of decrease of RBS for each depletion rate was dependent on *F*, the ratio of haul swept area relative to the size of the effective area. Therefore, a larger *F* occurred when the size of the haul was larger relative to the size of the effective area of the fishing lane. This could occur through vessels sweeping larger areas of seabed per haul than other vessels. This could also occur if a vessel did not fish considerable areas of a fishing lane which resulted in smaller effective area and therefore increased *F*.

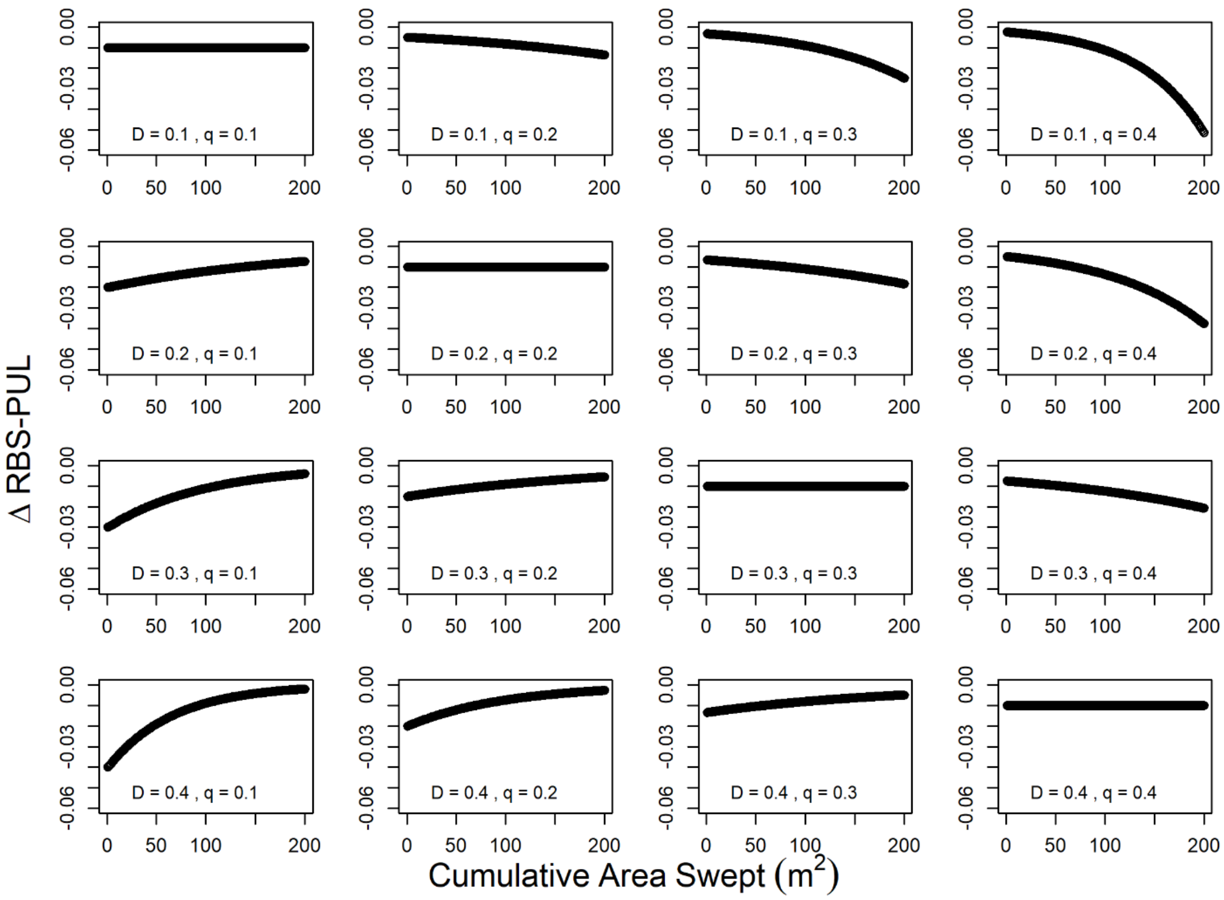


Figure 3.2: Simulated change in RBS per tonne of scallop catch landed (ΔRBS-PUL) plotted against cumulative effort (swept area, m²). In each panel the depletion rate (D) and vessel absolute catch efficiency (q) used in the simulation are printed.

ΔRBS-PUL

Our simulations of ΔRBS-PUL demonstrated that if the catch efficiency of a vessel was equal to the benthos depletion rate then the ΔRBS-PUL would be expected to remain constant with cumulative effort. Then if catch efficiency was lower than the depletion rate, there was an increase in ΔRBS-PUL with increasing cumulative effort. If catch efficiency was greater than the depletion rate then there was a decrease in ΔRBS-PUL with increased cumulative effort. This highlighted that highly efficient vessels will cause a greater environmental impact relative to their target catch by continually fishing an area. In contrast, this highlighted that vessels with lower catch efficiency will begin to reduce their environmental impact relative to their target catch as they repeatedly fish an area.

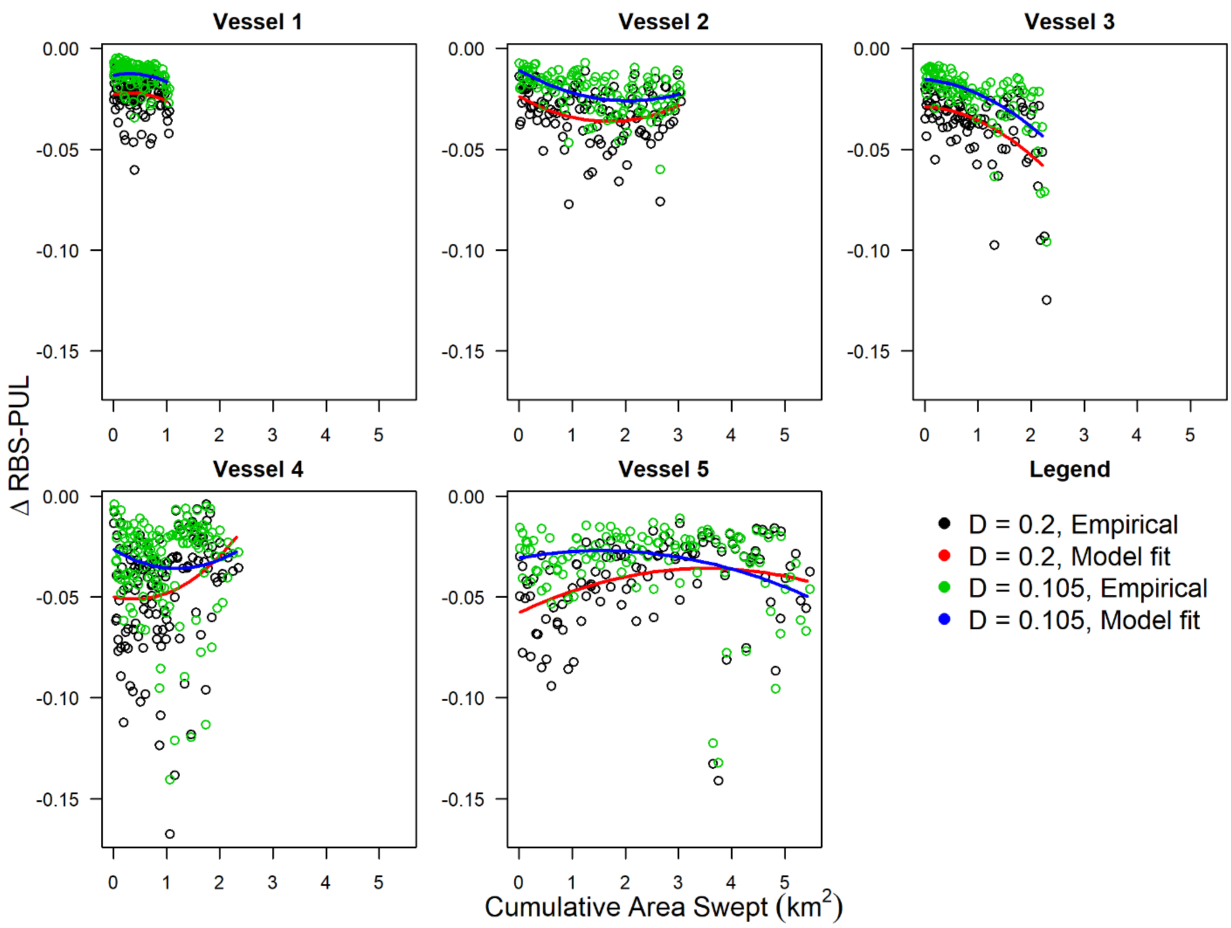


Figure 3.3: Empirical change in RBS per tonne of king scallop catch landed (ΔRBS-PUL) plotted against cumulative effort (swept area (km^2)) and separated by vessel, from the fishing intensity experiment. Cumulative effort is cumulative by fishing lane. Black points are individual hauls estimated using depletion rate D = 0.2, and red lines are model fits from a mixed effects model fitted to all data using depletion rate D = 0.2. Green points are individual hauls estimated using depletion rate D = 0.105, and blue line is model fit from mixed effects model fitted to all data using depletion rate D = 0.105.

The empirical estimations of ΔRBS-PUL calculated using the two depletion rates (D = 0.105 and 0.2) showed a variety of relationships with increasing cumulative effort, and these are likely to have varied between vessels because of each vessel's catch efficiency and the patterns in which the vessels fished each lane. The catch efficiencies of the vessels were estimated by individual fishing lanes in Chapter 2. The two catch efficiency estimates for Vessel 1 were q = 0.35 and 0.62. Therefore, these estimations agree that ΔRBS-PUL should (eventually) decrease with increasing cumulative effort (as indicated by the simulations) as these catch efficiencies are higher than either of the depletion rates. The initial increase in ΔRBS-PUL was likely caused the vessel fishing unfished ground during initial hauls. The catch efficiency estimate for Vessel 2 was q = 0.32, however the estimated ΔRBS-PUL began to increase, after an initial decrease, with increased cumulative effort which the simulations indicate should not happen. The same was also true of Vessel 4, which had catch efficiency estimates of q = 0.26, 0.35 and 0.47 and therefore were all greater than the depletion rates. Vessel 3 had catch efficiency estimates of q = 0.47 and 0.51 and ΔRBS-PUL decreased with increasing cumulative effort for both depletion rates, as should happen. Vessel 5 was the only vessel with estimated catch efficiency lower than one of the depletion rates (q = 0.13) and therefore ΔRBS-PUL should have increased with increased cumulative effort for the higher depletion rate. Instead ΔRBS-PUL began to decrease with increased cumulative effort after an initial increase, and this was the same for both depletion rates.

These discrepancies from the expected patterns highlighted by the simulations were caused by the manner in which the vessels fished each lane (i.e. non-consistent depletion patterns). Here we assumed that the depletion rate of a vessel on the benthos was independent of the catch efficiency, but it may have been that the depletion rate fluctuated between vessels and may be linked to the vessel catch efficiency. Research quantifying how depletion rates vary between vessels and how they are linked to their catch efficiencies is required to address this. The relationship between catch efficiency and depletion rate is important for understanding how the impact on the benthic invertebrate biomass changes per tonne of king scallop caught. If accurate depletion rates and catch efficiencies can be quantified, either by individual vessel or by similar vessels, and then by other factors, such as habitat type, then these could be used to help as evidence for trade-offs balanced between environmental efficiency and other efficiency measures such as catch, bycatch and fuel efficiencies.

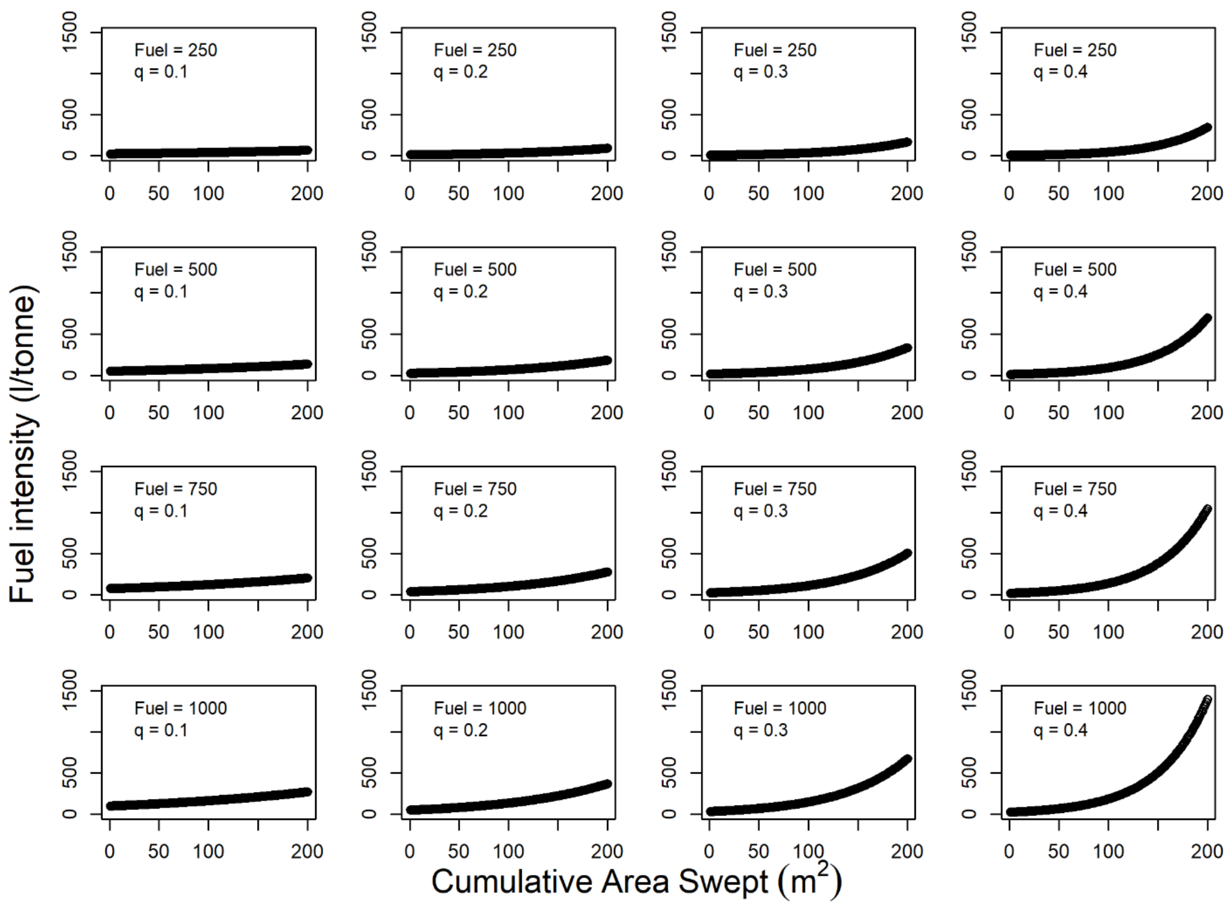


Figure 3.4: Simulated fuel intensity (l/tonne landed) plotted against cumulative effort (swept area). In each panel the fuel consumption (l) and vessel absolute catch efficiency (q) used in the simulation are printed.

Fuel intensity

Our simulations of fuel intensity showed increases of fuel intensity with increased cumulative effort in all cases (Figure 3.4). The rate of increase was dependent on the fuel consumption rate and the catch efficiency of the vessels. Across the three vessels where empirical fuel intensity was analysed, fuel intensity increased with increasing cumulative effort. Our simulations show this increase is expected as, regardless of vessel specific daily fuel rate, more fuel would be required to catch a tonne of king scallops as each area was depleted further and scallop density decreased. The empirical catch rates showed depletion patterns and were analysed and discussed in Chapter 2. The majority of empirical hauls had a fuel intensity estimate less than 500 l/tonne, and all of the remaining hauls had a fuel intensity less than 2000 l/tonne. However, it is key to stress that the vessels were instructed to fish longer in a fishing lane than they may have chosen to out with an experimental setting. As a consequence, we would expect to see fewer fuel intensities between 500 and 1000 l/tonne for an area of similar initial scallop densities out with an experimental setting.

Another important consideration is that the scallop catches in the present study were reported including shell weight, as is common for molluscs. This is important as species with a greater proportion of inedible live weight (e.g. a shell) will have a relatively lower fuel intensity compared to species with a higher percentage of live weight that is edible (such as finfish). Parker and Tyedmers (2015) reported global median fuel intensities for a range of fishing methods and species groups, although these are reported by live weight of the species rather than edible protein (Tyedmers 2001). As a consequence, we can directly compare our estimates to those of Parker and Tyedmers (2015) for molluscs, which were reported including shell weight, and dredge gears, as these gears are often used to capture molluscs. Parker and Tyedmers (2015) found that the global median fuel intensity of dredges was approximately 500 l/tonne and was between 500 and 1000 l/tonne for molluscs. Therefore, the majority of our by-haul fuel intensity estimates were lower than the global medians estimated by Parker and Tyedmers (2015) for dredge vessels and molluscs. The primary reason for this is likely to be the high density scallop sites chosen for this experiment, and these values demonstrate that scallop fishing in such high density areas is relatively fuel efficient compared to the global averages.

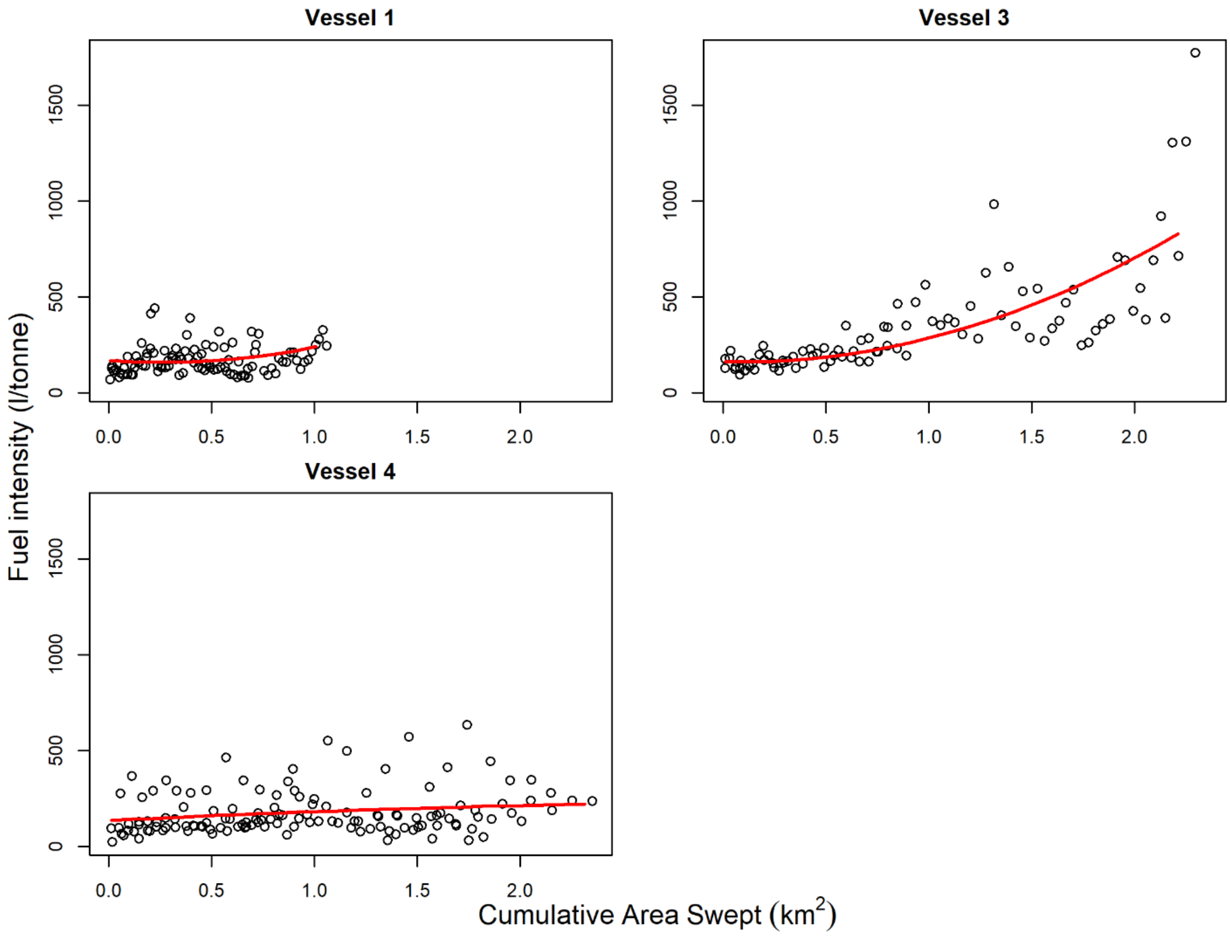


Figure 3.5: Empirical fuel intensity (l/tonne of scallops landed) plotted against cumulative effort (swept area (km^2)) and separated by vessel, from the fishing intensity experiment. Cumulative effort is cumulative by fishing lane. Black points are individual hauls and red lines are model fits from a mixed effects model fitted to all data.

Methodological considerations

The area of each fishing lane (1700m by 370m) was large compared to the width of a typical haul path of a vessel (14 dredges was 10.64m in width). Due to these relatively narrow haul paths some vessels conducted multiple hauls before passing over previously fished seabed or applied large amount of cumulative effort to one part of a fishing lane before moving to another relatively unfished part (as demonstrated in Chapter 2). This will explain unexpected increases or decreases in the estimated empirical ΔRBS-PUL and unexpected decreases in estimated empirical fuel intensity with increasing cumulative effort. For this reason, fishing lanes L8, L10 and L15 were removed from the analysis due to too less than 45 % of the seabed being swept. For the majority of fishing lanes, the high amount of cumulative effort applied had resulted in satisfactory overall trends of depletion. Therefore, although the estimates of ΔRBS-PUL and fuel intensity may not have been accurately estimated after each haul, due to the differences in fishing patterns, the overall trends with cumulative effort were satisfactory for supporting the simulations. More care of the spatial implications of these analyses would be required if specific parameters, such as a rate of change, were to be estimated.

This study area had been closed to commercial scallop dredging for five years prior to the experiment, and therefore relatively high densities of king scallops had accumulated (Chapter 2). High densities of king scallops was beneficial for the analyses here, as it allowed understanding of change in the reported efficiency metrics as the fishing lanes were repeatedly fished. However, in a commercially fished area initial densities may be far lower. If RBS is assumed to be relative to some unfished level, then the fishing may be occurring much further down the curves in Figure 3.1 and further to the right on the x-axis on any of Figure 3.2 and Figure 3.3 (i.e. after high cumulative effort has already been applied to an area). Lower scallop densities will also lead to greater values of fuel intensity, with the rate of increase in fuel intensity between hauls increasing more rapidly for a vessel with higher scallop catch efficiency (Figure 3.4).

Implications for management

To apply the work from this study as a management strategy, vessel catch efficiencies could be quantified and vessels classified by low, medium and high efficiencies. Then effort limits within areas could be set for vessels so that the environmental impact of any haul does not exceed a threshold relative to the amount of scallop catch (measured by ΔRBS-PUL). In this scenario, highly efficient vessels would be advised to fish areas lightly and less efficient vessels could be permitted to fish areas for longer. To implement this strategy greater understanding of individual vessel catch efficiencies and areas specific depletion rates would be required. In addition to the aforementioned methods for studying catch efficiency (Chapter 2), benthic depletion rates could be further studied by before-after-control-impact towed gear experiments (e.g. Hiddink et al 2006; Lambert et al 2017).

This management strategy could then be applied in a rotational management fashion in the Cardigan Bay king scallop fishery. Once an overall effort limit is met, based on the collective effort applied by the fleet, an area could be closed and another area opened. The effort limit may be set by catch or landings per unit effort, as in the Shetland king scallop fishery (Tindall et al 2016), or estimated as a limit on the amount of cumulative effort that may be applied to any given area. Vessel monitoring systems are available to monitor, in real time, the spatial patterns of vessels fishing within a given area (Wallace et al 2015), and there is advances in technology which permit real time catch and landings reporting (Little et al 2015). Therefore, the tools are available to monitor the efficiency of fishing and incorporate this in to management as is already done in multiple fisheries throughout the world (Little et al 2015).

The effort limit could also be determined from a trade-off of multiple efficiency objectives. The efficiency objectives could include both ΔRBS-PUL and fuel intensity, other measures of environmental impact, bycatch reduction and wider economic efficiencies. Potential effort limits to reduce environmental impacts for areas in this fishery have also been discussed by Lambert et al (2017), who analysed recovery four months after this experiment and found that fishing intensities > 6 (i.e. six times more swept area than the size of an area of seabed) on seabed communities was closest to the magnitude of natural disturbance in the area. This implied that all the fishing conducted during this experiment had a lesser effect than natural disturbances, although the authors discuss a precautionary approach towards identifying a seabed impact effort threshold. To help best optimise different efficiency objectives, including the seabed impact threshold identified in Lambert et al (2017) and the environmental and economic efficiency metrics reported in the present study, a more sophisticated efficiency analysis should be considered for the future. Such an efficiency analysis could be Pareto efficiency (Jacobsen et al 2017). Quantifying Pareto efficiency for this study may allow for determination of the amount of cumulative effort that could be applied to each of the areas used in this study which best meets the objectives of catch, bycatch, environmental and economic efficiencies collectively. Such an approach was not employed here, due to lack of data to conduct a full efficiency frontier framework, and the clear variation between vessels, but we believe this work could contribute to such an approach if attempted in the future.

Alternative efficiency metrics

The size-structure of king scallop catches was not monitored during all hauls in the experiment which meant we could not consider the issue of target species discarding. Whether target species survive after being discarded is an important consideration for the impacts of fishing (Davis 2002). If more individuals are killed by fishing than those in the landings then this should be incorporated in stock assessments to accurately estimate the stock size (Benoit et al 2010). Similarly, it is good environmental practice to reduce the amount of any animals killed by fishing which are not used for human consumption. This analysis only focussed on those king scallops which were landed (i.e. above the MLS and not badly damaged) and does not reflect on the efficiency of minimising discarded king scallops. The majority of discards would be expected to be under the MLS, and their survivability after discarding was beyond the scope of the dataset from the experiment. The efficiency of minimising discards is an important consideration for management but not one that was not addressed here. The focus on only marketable king scallops is still appropriate as this is what potential primary management measures are likely to focus on.

Conclusions

This work has demonstrated with simulations, and supported by empirical evidence, how a measure of environmental efficiency (ΔRBS-PUL) changed when an area was repeatedly dredged. In particular, we highlighted the importance of the relationship between the depletion rate of fishing on the benthos and vessel catch efficiency, and how the relationship between these two values will affect environmental fishing efficiency as an area is repeatedly fished. A consequent manage strategy could use knowledge of catch efficiencies of specific vessels to limit their environmental impact on areas of the fishery. We have also provided simulations and empirical evidence of how fuel efficiency, measured as fuel intensity, changed as an area was repeatedly fished, and demonstrated that king scallop dredge fuel intensity was lower here than median estimates from a global analysis of dredge and mollusc fisheries. This is also important from an environmental perspective, due to greenhouse gas emissions. The environmental and fuel efficiency evidence from this study could be incorporated in a future analysis to determine an effort limit for areas in a fishery which achieves highest possible efficiency across multiple objectives. Further quantification of both ΔRBS-PUL and fuel intensity across a greater range of vessels would be required to provide more evidence to support such trade-offs between environmental and fuel efficiencies when repeatedly fishing an area. The resultant effort limits could be directly incorporated in a potential effort-based rotational management strategy for a scallop fishery.

CHAPTER 4: A COMPARISON OF AGE-, LENGTH- AND UN-STRUCTURED INTEGRATED ANALYSIS MODELS FOR ASSESSING SCALLOP STOCK SIZE

Abstract

Single species stock assessments continue to play an important role in supporting fisheries management, yet data-limited situations can lead to uncertainty in their reliability. Here we compare the performance of three models in relation to a temporally data-limited scallop stock, based on the data available, population characteristics and model fit. All three models were integrated analysis (multiple observed datasets), stock assessment models based on different characteristics of stock structure (length-, age- and un-structured respectively). Unstructured models are also known as surplus production or biomass dynamic models. All models were designed to operate with aggregated catch data (single sum of annual catch) as well as survey data as either length- or age-frequencies or total index. The models were designed to account for the seasonal patterns in scallop life history and fishing activities. They were fitted to a short time series containing missing survey data. Both the age- and un- structured models estimated that stock size decreased with time, and at realistic and similar magnitudes. Both these models had the best goodness-of-fit. In contrast, the length-structured model had a poor goodness-of-fit and estimated that stock size was rapidly increasing with time. This was likely caused by the additional complexity of modelling growth and over-weighting of length-composition data in the joint likelihood. This work has provided the foundations for assessing Welsh scallop stock(s) size(s) using some of the most recent statistical stock assessment modelling tools and frameworks available. The posterior estimates of many model parameters, such as fishery selectivity curves and survey catch efficiency, can also be used as prior distributions in analyses in other king scallop fisheries. This work also demonstrated that age- and un- structured models can produce similar stock size estimates but that there still remains variability between all three stock assessment model estimates when applied over a short time series. This highlights the importance of carefully considering the estimated stock structure in stock assessment models.

4.1 Introduction

The sustainability of a fishery depends on the size of the target species stock over time, and both the socio-economic impact and the environmental impact of fishing (Hilborn and Walters 1992; Heino and Godø 2002; Hilborn 2005). The size of the target stock over time is typically measured as abundance or biomass (Hilborn 2005). From the trend of stock size, it is common to estimate concepts such as maximum sustainable yield (MSY), which can be used in target setting or to derive biological reference points to limit fishing activities and avoid overfishing of stocks (Jensen and Marshall 1982; Caddy 2004; Shertzer et al 2008). MSY is the largest amount of annual catch from the fishery that could be removed in perpetuity (Maunder 2008). Estimates of recent stock size, MSY and consequent biological reference points, can inform the use of management tools, such as catch limits or effort restrictions, to ensure the future sustainability of the target stock and fishery (Hilborn and Walters 1992). Despite the benefits of quantifying stock size, some important commercial fisheries cannot do so due to data deficiencies, or the lack of a suitable method of assessment (Carruthers et al 2014). Even commercially important species lack analytical assessments of stock status. For example, king scallop (*Pecten maximus*) management is not informed by stock assessments for the majority of stocks in the UK.

Stock assessment models are routinely used to estimate species stock size, as well as to provide other useful management metrics such as annual fishing mortality rates, annual recruitment, MSY and biological reference points. A variety of stock assessment techniques exist to estimate these management metrics and all involve the use of mathematical calculations and statistical methodologies designed to account for high variability and uncertainty in fishery -dependent and -independent data (Hilborn and Walters 1992). An important consideration is the choice in the way the mathematical calculations, or population dynamic equations, are structured in models (Hilborn and Walters 1992). The structure of models is linked to parameter estimation, with a more detailed structure allowing for estimation of more detailed parameters which may allow for a better representation of reality in the stock assessment model (Hilborn and Walters 1992; Bjorndal and Brasao 2006). The structure of the model determines whether the stock size is estimated as a single annual figure of biomass (unstructured) or whether the stock is simulated in groups consisting of fish that are similar in some respect (e.g. age or size) (structured).

One general stock assessment approach for estimating stock size is historical stock reconstruction from fishery data (Hilborn and Walters 1992). This approach estimates the initial stock size and then uses a mathematical model to estimate the abundance in consequent years in the time series (Hilborn and Walters 1992). The parameter values in the calculations are then adjusted to provide the best fit between observed and estimated data sets from the fishery (Hilborn and Walters 1992). In modern stock assessments, this requires statistical methodology and is often computed using a likelihood function (Maunder and Punt 2013). Unstructured historical reconstruction stock assessment models are also referred to as surplus-production or biomass dynamic models and are considered the simplest historical reconstruction stock assessment models due to the relatively few estimated parameters and less onerous data requirements than other stock assessment modelling options (Jensen and Marshall 1982; Hilborn and Walters 1992; Punt et al 2013). The population dynamic equations used to update the stock size over time in these models are often based on equations developed by Schaefer (1954), Pella and Tomlinson (1969) or Walters and Hilborn (1976).

The most common structured model technique is to estimate the stock size by fish of the same age, and these are known as age-structured models. Here, the population dynamic equations update the abundance in each age class over time. Age is a convenient way to structure the stock as it corresponds to (typical) yearly model time steps and annually reported landings (e.g. Fournier et al 1998; McGarvey et al 2010; Methot and Wetzel 2013). However, the lack of routinely available age data for fish stocks, and the potentially high measurement error in the aging of many fish species, has led to the development of length-structured stock assessment models (e.g. Sullivan et al 1990; Punt and Kennedy 1997; Punt et al 2010). Length data are generally easier to obtain and often have far lower measurement errors than age data (Sullivan et al 1990). In these models the abundance of fish in each length class is updated through time, and the detailed biological structure of the estimated stock is often maintained, or even enhanced, when compared with age-structured models (Sullivan et al 1990). However, modelling a fish stock by length-structure involves explicitly modelling growth as, unlike in age-structured models, fish can transition between classes within an annual model time step (e.g. Punt et al 1997; Maunder 2001; Punt et al 2013).

Unstructured models have particularly been used in tuna stock assessments, other similar finfish stocks and extensively for shellfish (Punt et al 2013), yet many consider their population dynamic equations too simple to capture the complexity of biological reality and argue that a structured stock assessment should always be implemented over unstructured stock assessments where data are available to do so (Hilborn and Walters 1992; Quinn and Deriso 1999; Tahvonen 2009). Despite this strong criticism Hilborn and Ledbetter (1979) demonstrated that poor fits in unstructured models were often due to poor relationships between stock size and fishing effort, which caused fitting problems in age-structured alternatives as well. In addition, several studies have shown that unstructured models can produce similar management parameter estimates to, or even more reliable ones than, age-structured alternatives (Ludwig and Walters 1985; 1989; Moxnes 2005). However, there are also examples where unstructured models have been shown to be incapable of accurately estimating stock size (Townsend 1986; Bjorndal and Brasao 2006; Tahvonen 2008). The variability in these experiences with different models suggests that the choice of an appropriate and reliable modelling approach is context and data dependent.

Although age-structured methods are particularly common, they are not without critique. Some age-structured techniques are implemented in the absence of age data. For example, it is possible to use a 'slicing' technique to assign size-composition data to age-classes if it is desirable to use an age-structured model (e.g. McGarvey et al 2007). This technique assigns age-classes based on measured growth rates (McGarvey et al 2007). Slicing techniques can lead to a significant loss of information and so true length-structured models, where all calculation processes are kept length-based, are preferable (Punt et al 2013). Another disadvantage of age-structured methods can occur in a MLS managed fishery if the model uses an age-based selectivity curve method, as is common (Punt et al 2013). Selectivity curves are used in stock assessments to describe the proportion of caught fish that are retained in the gear per length or age class. In an MLS managed fishery, at least one age class of fish will span the MLS. In the fishery the true underlying length-at-age distribution of such an age class will become skewed towards the individuals lesser than the MLS (as those ≥ MLS will be landed) and this skewness is unlikely to be captured in a stock assessment model using an age-structured selectivity curve (Punt et al 2013). As a consequence, individuals < MLS in the MLS overlapping age-class will be removed from the estimated stock at a higher rate than occurs in reality (Punt et al 2013). This can result in an overestimation of biomass in age classes spanning the MLS, as the larger individuals and heavier individuals in the age class are more likely to have been landed in reality. The 'slicing' technique can overcome this; however, the resultant age-structured model becomes similar in complexity to length-structured models with the incorporation of growth rates (Punt et al 2013). In a length-structured model, the size-groups can be set precisely enough to capture the knife-edged selectivity effect of a MLS without manipulation of the raw data prior to model fitting (Punt et al 2013).

Analytical disadvantages of length-structured models also exist. Length-structured models do not track cohorts of fish and typically have many more classes than age-structured models which leads to increased complexity and can lead to worse performance (Punt et al 2013). In addition, length-structured models must explicitly model growth which increases model complexity (Hillary and Eveson 2015) and can considerably increase the computational run time of length-structured models. If growth is poorly described then length-structured models are likely to perform worse than age-structured equivalents (Punt 2003; Punt et al 2013). Furthermore, unless tagging data are available to estimate growth rates then age data are required to estimate the growth rates required in length-structured models. This means length-structured models are often not entirely independent of age.

Whether using length-, age- or un-structured population dynamics equations, there are many options for the statistical framework under which the stock assessment models are implemented. A field of stock assessment models known as integrated analysis (IA) models use multiple data sources and a joint likelihood function to estimate model parameters and stock size (Methot and Wetzel 2013). The population dynamics equations in these models estimate the stock size through time based on the fundamental dynamics of growth, maturity, morality and recruitment, whilst modelling process error (Punt et al 2013). Process error is the natural variation in the true stock dynamics, and differs from observation error which is the error in the methodology (Ahrestani et al 2013). The IA method for stock assessment has several advantages over other methods such as cohort analysis or virtual population analysis (VPA). Firstly, there is no assumption that the stock must be in a steady state (Sullivan et al 1990; Punt et al 2013). Secondly, by analysing multiple data sources simultaneously logical consistency between data sources is best maintained (Maunder and Punt 2013). Thirdly, IA models also provide an explicit and more complete estimation of the uncertainty involved in stock assessment calculations, which may be considered crucial in management decisions (Maunder and Punt 2013). However, despite the considerable analytical advantages of IA models, their complexity may make them challenging to understand for both managers and biologists (Maunder and Punt 2013; Punt et al 2013). Like many approaches, IA models may also become subject to poor performance if key parts (such as growth) are poorly described (Punt et al 2013). In addition, and also like other methods, IA models are subject to poor performance if considerably inconsistent data sources are used (Punt et al 2013).

Length-, age- and un-structured models have been implemented for scallop fisheries across the world and the majority of which were IA models. Delay-difference models, which typically split the stock in to two stages (such as lower than MLS and above), are extensions of unstructured models and have been used in multiple scallop fisheries (Nasmith et al 2016; Bloor et al 2017). Scallops can often be aged by counting external growth rings on their flat shell (Haskin 1954; Campana et al 2001) which has resulted in the use of age-structured models in other scallop fisheries (Campbell et al 2012; Dobby et al 2017). However, the growth rings are not always visible and there is a risk of observation error, hence length-structured models have also been implemented in scallop fisheries (Williams et al 2010; NEFSC 2014).

This present study compared the performance of each an age-, length- and un- structured IA stock assessment model for estimating the size of a Welsh scallop stock. The population dynamics equations were extremely similar between the length- and age-structured models, whereas the unstructured model population dynamics equations differed more. Each model used the same computer estimation algorithm and statistical framework for parameter estimation. All common fixed parameter values and assumptions were kept as similar as possible between the models. The commercial fishery data were identical between the three models and the survey data was from the same source but arranged according to model structure. Each of the length- and age-structured models estimated total stock abundance, total stock biomass (TSB), spawning stock biomass (SSB), fishing mortality and recruitment, from which MSY, B_{MSY}, F_{MSY} and carrying capacity were derived. These were then compared with the outputs of the unstructured model that provided only TSB, MSY, B_{MSY}, F_{MSY} and carrying capacity. The length- and age-structured models also estimated length- or age-structured fishery selectivity, fishery retention (catch which was not discarded) and survey absolute catch efficiency curves. The unstructured model also estimated survey absolute catch efficiency and fleet catchability. This research also estimated von Bertlanffy growth, age- and length- weight and age- and length- at-maturity curves prior to model fitting, as these were required for some of the models. Each model was fitted to the available data which spanned a relatively short time series (five years), which contained missing survey data in one year. The models were evaluated on their statistical goodness-of-fit to the observed data and the magnitude and trends with time of the key outputs.

The research aimed to highlight the importance of carefully considering modelled stock structure when estimating stock size. This research also aimed to assess the suitability of each stock structure method for the Welsh king scallop fishery, and help guide future data collection and model improvements. In addition, it was intended that many of the parameters estimated by the models were likely to be directly useful in other analyses of this fishery or as prior distributions in other king scallop fisheries.

4.2 Materials and Methods

Assessment area

Each model was fitted to observed data from a temporally data-limited king scallop (*Pecten maximus*) stock in the areas open to commercial scallop dredging of the International Council for the Exploration of the Seas (ICES) statistical rectangle 33E5 (hereafter referred to as the assessment area), which is situated in Cardigan Bay, Wales, UK (Figure 4.1). The assessment area does not include areas of this rectangle which were closed to commercial scallop dredging (Figure 4.1). King scallop fishing in Wales is currently managed using input controls such as gear (Newhaven dredges), MLS and effort restrictions which are not linked to a stock assessment (The Scallop Fishing (Wales) (No. 2) Order 2010, Table 1.8).

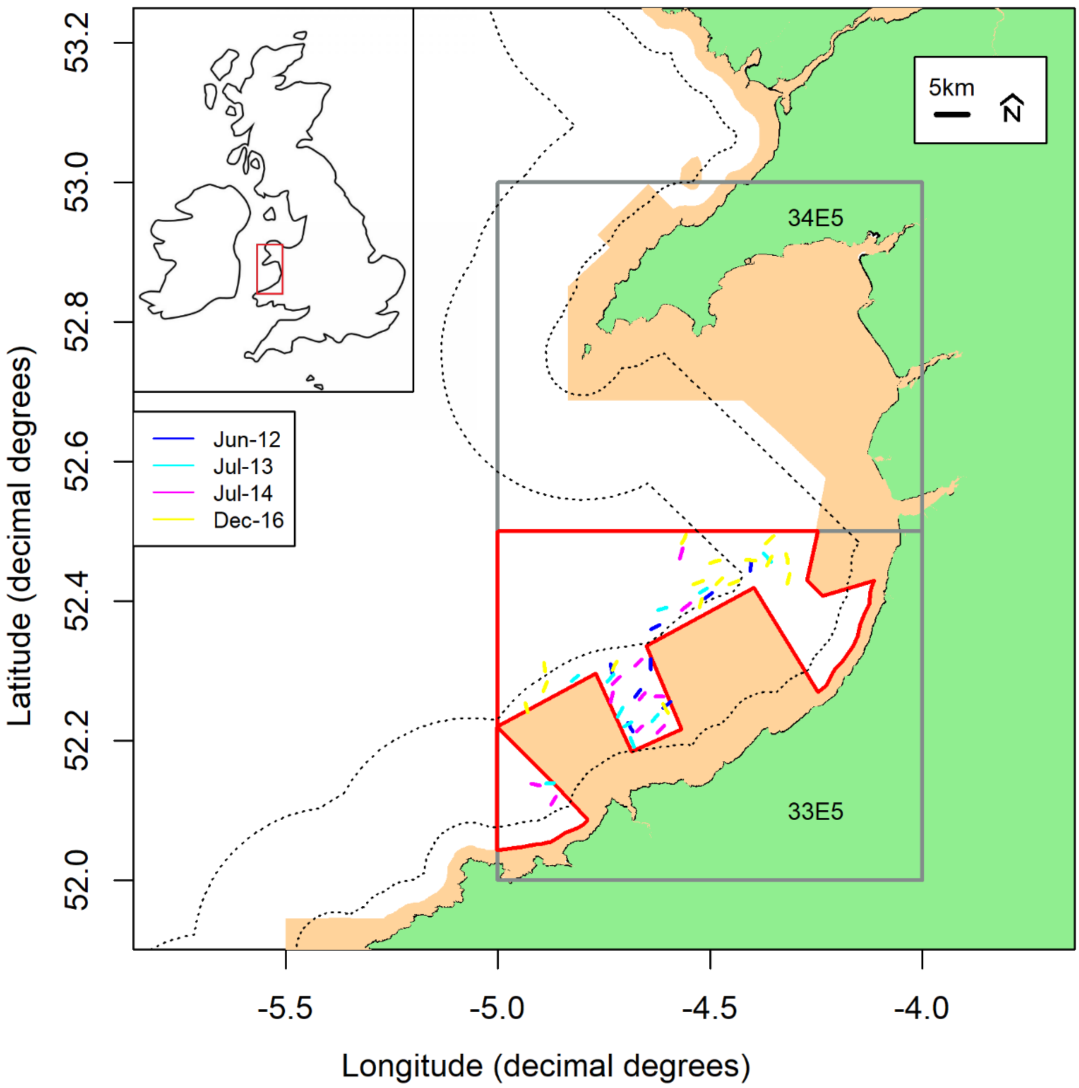


Figure 4.1: The location of the stock assessment area (areas included within red lines) within Cardigan Bay, Wales. The assessment area is 1,372 km^2. Green is land, orange areas are closed to scallop dredging and the dashed lines represent the 3nm and 12nm distance from shore lines. Between the land of Wales (right side green) and the 12nm line is Welsh waters, and further from the coast and beyond the 12nm line are European Union waters. White area is sea open to commercial scallop dredging. Survey hauls are coloured according to year as indicated in the map legend. Two ICES statistical rectangles are outlined in grey and named on the map (note the north and west edges of 33E5 are mostly coloured red as these are also the north and west edges of the assessment area). The inset map shows the location of the main map within the British Isles.

ICES statistical rectangle 33E5 was chosen because it had considerably higher annual landings across the time series than other ICES statistical rectangles that are partly in Welsh waters, and therefore represented a key component (approximately one third) of the greater Welsh scallop fishery. ICES rectangles were convenient so that the total landings from them could be defined, and there were no finer scale landings data available. ICES rectangle 33E5 does not cover the entirety of Cardigan Bay, and therefore the focus on this rectangle alone excludes parts of the Cardigan Bay stock that fall outside the rectangle (to the north). The ICES rectangle immediately north of 33E5, 34E5, spans in to another fishing ground (Llyn Peninsula ground) and therefore it was impossible to separate the landings from the Llyn Peninsula and Cardigan Bay fishing grounds. It is currently unclear if the population in the Llyn Peninsula ground is part of the same stock as the Cardigan Bay population. Genetic evidence suggests that the Cardigan Bay population is isolated from the other Welsh king scallop grounds, but biophysical modelling suggests that Cardigan Bay is a sink for larvae from the Llyn Peninsula ground (Hold et al in press). Therefore, the degree of isolation of the Cardigan Bay population remains unclear. Additionally, including 34E5 would result in large areas included in the stock assessment where there is no king scallop fishing based on knowledge of fishing grounds (Figure 1.5). As a consequence of this combined uncertainty 34E5 was not included in the assessment area, which meant that the portion of the Cardigan Bay stock in the 34E5 rectangle were also not included. Survey indices from this area indicated king scallop densities to be relatively low (annual mean of 0.24 to 0.82 king scallops ≥ MLS per 100m^2) (Delargy et al 2019), and therefore, although not ideal, the assessment area was constrained to (the open parts of) 33E5 to best quantify the landings taken from the stock. The assessment area was also chosen because fishery-independent dredge surveys have been conducted there since 2012 (Figure 4.1) (Delargy et al 2019).

Brief overview of models

Each model consisted of population dynamics equations used to estimate the king scallop stock size over the time series. The equations and parameters of each model are detailed in the forthcoming subsections. Parameters for each model were either fixed and provided as inputs, or estimated when fitting the model using a Bayesian approach. A Bayesian approach requires prior statistical distributions of each of the estimated parameters to be provided by the user. For each model, the population dynamics equations were then fitted to observed data, to estimate the joint posterior statistical distribution of the model estimated parameters (McAllister and Ianelli 1997). The fitting procedure sampled values from each estimated parameter prior distribution, and the probability of a given set of values generating predicted data which reflects the observed data was evaluated through a joint likelihood function and the specified prior distributions (McAllister and Ianelli 1997). The structure of the population dynamic equations is described in the flow diagram for the length-structured model (model with most parameters) for a single set of estimated parameter values (Figure 4.2).

Observed data used for fixed parameters and likelihood evaluation

Annual estimates of total catch of king scallops (including shell weight (live weight), tonnes) were obtained from the assessment area for the years 2012 to 2016. Catch data consisted of official landings (STECF 2018) and discards estimated using discard rates (unpublished data from Marine Institute, Galway) (Table 4.1). Discard rates were available from 2011, 2012, 2013 and 2017. The discard rates for 2014 to 2016 were estimated from a general linear model fit to the relationship between known discard rates and years. The discard rate informed the percentage of the catch which was discards and the percentage which was landings, for the years 2012 to 2016. Discards (live weight, tonnes) for these years were then estimated using the amount of tonnes equating to a percentage of the total catch, which could be derived from the landings. In addition, annual estimates of effort (all sizes of vessels, hours fished) in the assessment area were obtained for the years 2012 to 2016 for vessels fishing with dredges (STECF 2018). Effort was used to derive annual catches in the unstructured assessment model and incorporated as fixed parameters.

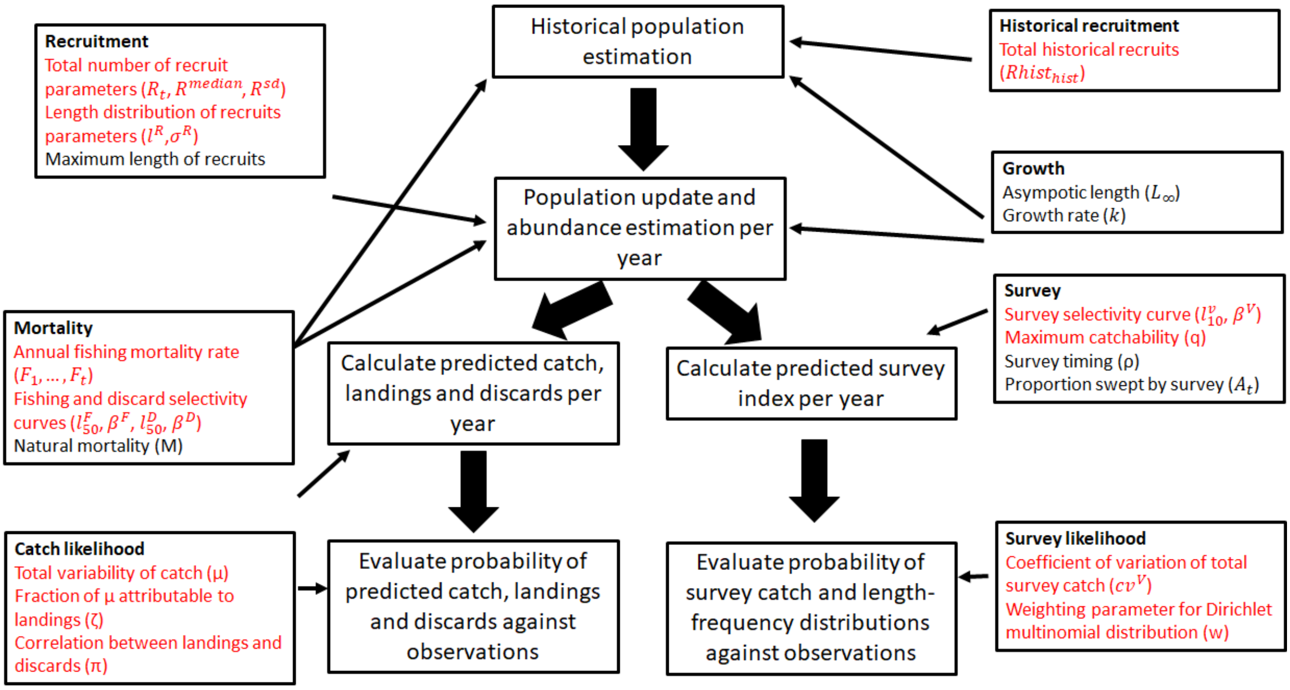


Figure 4.2: Flow chart of the length-structured model for a single set of estimated parameter values. Beginning at the top centre with the historical stock estimation and following the thicker arrows to the likelihood evaluation at the bottom centre two boxes. The boxes on the left- and right-hand sides detail all the estimated parameters (red) and key fixed parameters (black) used in the length-structured model calculations, and the thin arrows indicate where in the length-structured model process these parameters are used. The process is then repeated for multiple sets of estimated parameter values.

Fishery-independent survey indices and age and length distributions were obtained from annual surveys that followed a random sampling design in the assessment area. The surveys were not specifically designed for stock assessment of the assessment area, and instead sampled the areas outlined in Figure 1.5 which overlap with a large proportion of the assessment area. Positions were randomly selected from a grid overlaid on these survey areas. Only the survey hauls which fell within the assessment area were used in the stock assessment models here (Figure 4.1). No hauls from the SAC were included in the stock assessment models.

Table 4.1: Discard rates as percentage of king scallop catch from observers on board vessels fishing for king scallops with Newhaven dredges in the stock assessment area (unpublished data from Marine Institute, Galway).

Year	Discard rate (percentage of catch %)	Used in models
2011	10.0 (actual)	No
2012	7.3 (actual)	Yes
2013	4.6 (actual)	Yes
2014	3.8 (estimated)	Yes
2015	3.1 (estimated)	Yes
2016	2.3 (estimated)	Yes
2017	1.5 (actual)	No

Each survey was conducted from the RV Prince Madog and sampled using two Newhaven dredges. Each dredge had 10 teeth of 60mm in length and 60mm belly ring diameters, which differs from the commercial gear which have eight teeth of 110mm in length and wider belly rings (exact size varies). The dredges used in the surveys were designed to catch a greater number of king scallops less than the MLS compared to the commercial gear, which allowed for a greater understanding of the stock size structure. The survey data time series covered 2012 to 2014 and 2016. Abundance survey indices (total number of king scallops caught), and age or length distribution as relative proportions, were included in the joint likelihood function of the length- and age-structured models respectively. Only survey indices (expressed as total biomass of king scallops caught, live weight) were used in the unstructured model joint likelihood. Total numbers and biomass were not standardised, but total survey effort, expressed as the annual proportion of the assessment area swept, was used to estimate survey data in each model as described in the survey calculation equations.

In 2012 to 2014, the shell widths of up to 45 king scallops per dredge per haul were measured to the nearest mm and these same scallops were aged, by counting external growth rings. If more than 45 king scallops were caught in a single dredge then the frequency distributions were raised by the ratio of the total weight of king scallops caught in that dredge to the weight of the 45 measured. In 2016 up to 90 king scallops were measured and aged, and the frequency distributions were raised if more than 90 were caught in a single dredge by the same method. Each of the length and age distributions included the same king scallops caught during the surveys. These age data were also used to determine the fixed von Bertalanffy growth parameters used to estimate king scallop growth in the length-structured model.

Samples of king scallops were retained across the surveys (total of 472 individuals) and individually weighed (live weight). From these data the fixed parameters of an age-weight relationship and a length-weight relationship were estimated. These parameter estimates were used in age- and length- structured models respectively. The scallops in this sample were then dissected and maturity stage was quantified using the gonad observation index (Mason 1958). From these data the parameters of age- and size- at-maturity curves were estimated, which were required to estimate SSB after stock assessment model fitting in the age- and length- structured models respectively.

Structure of the models

The length-structured model was based on a length-structured model developed by Hunter (2015) for Scottish finfish stock assessment, which in turn was based on the length-structured model by Sullivan et al (1990). The length-structured model here is therefore similar to the CASA model used in the US sea scallop fishery (NEFSC 2014) which was also based on Sullivan et al (1990). The Hunter (2015) model was adjusted here to account for missing survey data, to allow growth parameters to be included as fixed parameters, instead of estimated parameters, and to account for the seasonality of the Welsh king scallop fishery and life history. The age-structured model was a modified version of the length-structured model so that it could operate in age classes. The equations from the age-structured models are presented here and can be assumed to be the same and operate with length classes for the length-structured model unless otherwise stated. The length-structured model also had additional components for describing growth and recruitment. The age-structured model estimated 11 classes from age two to age 12, whereas the length-structured model estimated the stock in 1 mm size classes which resulted in 166 classes. The age-structured model began at age class two so that recruitment was consistent in each of the length- and age-structured models, and so that recruitment represented king scallops which could be caught be either the survey or fishery. Age 12 acted as a plus group in the age-structured model, where surviving individuals were retained in this age class for the next year.

Each of the age- and length- structured models estimated stock size using population dynamics equations based on growth, mortality and recruitment. Although growth was not explicitly modelled in the age-structured model, it was implicitly modelled by moving surviving individuals to the next age class during each time step. In each model (age- and length- structured) the stock abundance (*N*) was updated at age (*a*) (and can be assumed length (*L*)) over time (*t*) based on growth (*P*), total mortality rate (*Z*) and recruitment (*R*), as is common in stage-structured fish stock modelling. In the age-structured model the growth parameter moved all surviving individuals to the next age class. The estimation of each of growth, total mortality rate and recruitment are described in consequent sub-sections. The updating of *N* occurred in three stages within a single time step (year) in both models to capture the seasonality of the fishing season and king scallop life history. This three-stage approach also allowed both models to operate in calendar years, which was how the commercial data was reported, as opposed to fishing seasons. The first stage ($N1_{a,t}$) updated the stock for the period 1st January to 30th April by applying half of the total fishing mortality rate (*F*), a third of the total natural mortality rate (*M*) and no growth or recruitment (Eq 4.1). Half of the total fishing mortality rate was applied at this stage as these four months were likely to represent similar landings to the other two months of fishing in the year (November and December) (Pantin et al 2015), and the fishery is closed from the 1st of May until the 31st of October annually. No growth or recruitment were applied at this stage as the majority of king scallop growth and recruitment takes place in the late spring and summer where there is greater food availability (phytoplankton) (Chauvaud et al 2012).

$$N1_{a,t} = N_{a,t}e^{-\left(\frac{1}{2}F_{a,t}+\frac{1}{3}M\right)} \; for \; t > 1 \tag{4.1}$$

The second stage ($N2_{a,t}$) updated the stock for the closed season period 1st May to 31st October by applying zero fishing mortality rate, half the natural mortality rate and all growth and recruitment (Eq 4.2). This period represented the closed fishing season and the late spring and summer months.

$$N2_{a,t} = N1_{a,t}P_a e^{-\frac{1}{2}M} + R_{a,t} \; for \; t > 1 \tag{4.2}$$

The third stage ($N_{a,t+1}$) updated the stock for the period 1st November to 31st December by applying half the fishing mortality rate, a sixth of the natural mortality rate and no growth or recruitment (Eq 4.3). This period represented two months of fishing where landings were expected to be relatively high compared to other months of the fishing season (Pantin et al 2015).

$$N_{a,t+1} = N2_{a,t}e^{-\left(\frac{1}{2}F_{a,t}+\frac{1}{6}M\right)} \; for \; t > 1 \tag{4.3}$$

Due to high variability in the observed data, the initial abundance ($N_{a,1}$) was likely to be inappropriate if estimated directly as an estimated parameter in each model. Therefore, a historical stock was estimated within each model over an artificial time series, to allow each model time to 'stabilise' and estimate a realistic initial stock size. This is often referred to as a 'spin-up' period, where a time-series model is given time to equilibrate and generate a suitable starting value that is consistent with the model's calculations (Thornton and Rosenbloom 2005). To do this, a historical stock ($N_{a,hist}$) was updated over historical time (*hist*) using estimated fishing mortality rates from the earliest year in the time series (*t*=1) (Eq 4.4). The historical recruitment values (R_{hist}) were estimated parameters in both models and were then entered to age or length classes as described in the *Recruitment* section. The initial historical recruitment ($R_{a,hist=1}$) was set as the initial historical stock ($N_{a,hist=1}$), applied across age or length classes.

$$N_{a,hist} = (N_{a,hist-1}P_a e^{-(\frac{1}{2}F_{a,1}+\frac{1}{3}M)} + R_{a,hist})e^{-(\frac{1}{2}F_{a,1}+\frac{2}{3}M)} \; for \; hist > 1 \tag{4.4}$$

The final historical stock ($N_{a,hist=n}$) was then set as the initial stock abundance ($N_{a,1}$) for the actual time series in each model (i.e. 2012). The length of the artificial historical recruitment time series (n) used to generate the initial abundance in the each model ($N_{a,1}$) was four years, as this allowed enough time for both models to generate a suitably sized initial stock. This artificial historical stock approach also reduced user bias in the estimation of $N_{a,1}$, which could each have been implemented as an estimated parameter. By treating $N_{a,1}$ as an estimated parameter, user bias from the prior distribution would have been incorporated in each stock size estimate for 2012. Under this artificial historical stock approach, the user bias was incorporated in the R_{hist} parameters and the models were given sufficient time to move away from these prior distributions and identify the likely true values of $N_{a,1}$. A similar approach to estimating initial stock size and structure was implemented in the length-structured model of Tasmanian rock lobster (*Jasus edwardsii*) (Punt and Kennedy 1997). For each model, longer artificial historical recruitment time series were tested but did not improve model performance, and therefore the four-year historical time series was chosen to minimise the number of estimated parameters.

The unstructured model differed from both the age- and length- structured models as growth, natural mortality and recruitment were not explicitly estimated, but instead estimated using a logistic biomass dynamic model (Schaefer 1954, Hilborn and Walters 1992). The unstructured model estimated the stock size as TSB (live weight, tonnes) over time (t) based on the intrinsic stock growth rate (r), carrying capacity (K) (live weight, tonnes), fleet catchability (q^F) and observed effort (E) (hours fished). The updating of *TSB* over time occurred in three stages within a single time step (year) to capture the seasonality of the fishing season and king scallop life history, and to ensure consistency with the age- and length- structured models. The first stage (*TSB1*) updated the stock by applying half the observed fishing effort (E), and no growth, natural mortality or recruitment (Eq 4.5). Half the observed effort was applied at this stage to reflect the half of the fishing mortality rate applied at this stage in the other two models. This assumed effort was directly proportional to fishing mortality rate, as is a common assumption.

$$TSB1_t = TSB_t - \tfrac{1}{2}(q^F TSB_t E_t) \; for \; t > 1 \tag{4.5}$$

The second stage (*TSB2*) updated the stock by applying all growth, natural mortality and recruitment (Eq 4.6). As growth, recruitment and natural mortality were not explicitly modelled by these equations they could not be divided by parts of the year as they were in the age- and length- structured models.

$$TSB2_t = TSB1_t + rTSB1_t\left(1 - \tfrac{TSB1_t}{K}\right) \; for \; t > 1 \tag{4.6}$$

The third stage (TSB_{t+1}) updated the stock by applying half the observed effort, to reflect the half of the fishing mortality rate applied at this stage in the other two models (Eq 4.7). Each of *r, K,* q^F and the TSB in 2012 ($TSB_{t=1}$) were estimated parameters in the model.

$$TSB_{t+1} = TSB2_t - \tfrac{1}{2}(q^F TSB2_t E_t) \; for \; t > 1 \tag{4.7}$$

Growth

Growth was not modelled explicitly in the age-structured model, and all surviving king scallops in a given age class were moved to the next age class during the closed season period. In the plus group (age 12) surviving individuals were retained. King scallops lay annual external shell growth rings in the late spring in the Irish Sea, therefore the increase in modelled age during the closed season is realistic and best ensures the ages between estimated and observed survey data were consistent. Growth was included in the unstructured model as part of Eq 4.6.

Mean growth increments in the length-structured model were modelled using a von Bertalanffy curve, which was transformed to be independent of age (Eq 4.8). Growth was therefore defined from the initial length structure of the estimated stock and the two von Bertalanffy parameters L_∞ and *k*, which represented the asymptotic length and growth rate respectively. Variation in growth rates of individual scallops at each length were incorporated by the specification of unique, log-normal distributions for each length. The two growth parameters were fixed parameters estimated by fitting a von Bertalanffy curve to king scallop age and length data obtained during the research surveys across all years in the assessment area. This curve was fitted using nonlinear least squares estimation and the FSA package for R (Ogle et al 2018).

$$\Delta L_L = (L_\infty - L_L)(1 - e^{-k\,t}) \tag{4.8}$$

The von Bertalanffy curves in the length-structured model forced the growth rate to decrease with increased length, which is an accurate representation of scallop growth (Chauvaud et al 2012). The decrease in growth rates with length, combined with the unique log-normal distributions for each length, resulted in a reduction in the variation in growth increments in larger scallops in the model. This reduction in growth increment variability is also realistic, as the largest scallops would have grown at more similar rates (Chauvaud et al 2012).

Mortality

The age- and length- structured models estimated age- or length- dependent, annual total mortality rates in an identical manner. Therefore, all reference to length classes can be directly substituted for age classes. Total mortality rates in both these models were the sum of fishing and natural mortality rates. The annual natural mortality rate was assumed to be constant with time and independent of king scallop age or length, as is common in stage-structured models (Punt et al 2013).

Age- and length- dependent fishing mortality was estimated by year as the product of annual fishing mortality rates and commercial fleet selectivity at age or length (s_a^F or s_L^F). Selectivity at age and length were estimated using a logistic curve (Eq 4.9) (where *L* may be substituted for *a*). The shape (a_{50}^F or l_{50}^F) and scale (β^F, same name in each model) parameters of each logistic curve were estimated parameters in both models. The annual fishing mortality rates represented the mortality rate applied to older or larger scallops that were fully selected and retained by the fishery, and these were estimated parameters in both models for each time step (F_1 … F_t).

$$s_a^F = \frac{1}{1 + e^{-\ln(9)\left(a - a_{50}^F\right)\frac{1}{\beta^F}}} \tag{4.9}$$

In both models, annual catches were then estimated using two-stage Baranov catch equations (Baranov 1918) (where *ρ* represented the fraction of the year and where *L* may be substituted for *a* to distinguish between the two models) (Eq 4.10 and Eq 4.11). Both equations used fishing ($F_{a,t}$ or $F_{L,t}$) and natural (*M*) mortality rates and the estimated age- or length- structured abundance. The first stage estimated the catches from the period 1st January to 30th April (Eq 4.10) and the second stage estimated the catches from 1st November to 31st December (Eq 4.11). This two-stage catch approach allowed summer recruitment, growth and natural mortality to be applied in the population dynamics equations before the November-December catch was calculated.

$$C1_{a,t} = \frac{\frac{1}{2}F_{a,t}}{\frac{1}{2}F_{a,t} + \frac{1}{3}M}\left(1 - e^{-\left(\frac{1}{2}F_{a,t}+\frac{1}{3}M\right)}\right)N_{a,t} \quad for\; 0 < \rho < \frac{1}{3} \tag{4.10}$$

$$C2_{a,t} = \frac{\frac{1}{2}F_{a,t}}{\frac{1}{2}F_{a,t} + \frac{1}{6}M}\left(1 - e^{-\left(\frac{1}{2}F_{a,t}+\frac{1}{6}M\right)}\right)N2_{a,t} \quad for\; \frac{5}{6} < \rho < 1 \tag{4.11}$$

The annual catch-at-age (or length) ($Cn_{a,t}$) was obtained by the summation of $C1_{a,t}$ and $C2_{a,t}$ before separation in to landings and discards. A logistic curve was used to estimate the retention fraction at age or length, and both the shape (a_{50}^{D}or l_{50}^{D}) and scale (β^{D}, same name in each model) parameters of this curve were estimated in both models (Eq 4.12). The product of the retention fraction-at-age (s_a^D) and $Cn_{a,t}$ resulted in the landings-at-age ($Ln_{a,t}$). Discards-at-age ($Dn_{a,t}$) were consequently estimated by subtracting $Ln_{a,t}$ from $Cn_{a,t}$

$$s_a^D = \frac{1}{1 + e^{-\ln(9)\left(a - a_{50}^D\right)\frac{1}{\beta^D}}} \tag{4.12}$$

Both $Ln_{a,t}$ and $Dn_{a,t}$ were converted to mean biomass-at-age (live weight, tonnes) ($Lb_{a,t}$ and $Db_{a,t}$) by multiplication with mean weight-at-age (or mean weight-at-length in the length-structured model). The two fixed parameters of the weight-age relationship used to estimate mean weight-at-age (*x* and *y*, Eq 4.13) were estimated using a general linear model on individual scallop weight and age caught in the assessment area during the surveys. The two fixed parameters of the weight-length relationship used to estimate weight-at-length (*a* and *b*, Eq 4.14) were estimated using a general linear model on natural logarithm transformed individual scallop weight and length caught in the assessment area during the surveys. Each of $Lb_{a,t}$ and $Db_{a,t}$ were summed across age classes (or length classes) to obtain estimated aggregated landings (Lb_t^{est}) and discards (Db_t^{est}) for each time step. Both Lb_t^{est} and Db_t^{est} were included in the likelihood function and modelled with a multivariate-normal distribution, where τ consisted of both $Lb_t^{est}$and Db_t^{est}, to represent estimated annual catch (Cb_t^{est}) (Eq 4.15). A covariance matrix (δ) was included in the likelihood function and estimated from the products of the coefficient of variation (CV) of each landings (cv^L) (single value) , discards (cv^D) (single value) and the correlation between the landings and discards (π), the latter of which was a fixed parameter in both models set at 0.95 to reflect high correlation between landings and discards. cv^L was the product of the total variability in the catch (μ) and fraction of this variability attributable to the landings (ζ), both of which were estimated parameters in both models. cv^D was the product of μ and the fraction of μ attributable to the discards ($1 - \zeta$).

$$W = y + x * \sqrt{a} \tag{4.13}$$

$$W = aL^b \tag{4.14}$$

$$ln(Cb_t^{obs}) \sim multinom(ln(\tau), \delta) \tag{4.15}$$

In the unstructured model, annual catch (Cb_t) (live weight, tonnes) was estimated as the sum of the total catch from each part of the annual fishing season (1st January to 30th April and 1st November to 31st December) using seasonal TSB, q^F and half of E_t (Eq 4.16). This approach assured consistency with Eq 4.5, 4.6 & 4.7 and the age- and length- structured models.

$$Cb_t = \frac{1}{2}(q^F TSB_t E_t) + \frac{1}{2}(q^F TSB2_t E_t) \tag{4.16}$$

Annual landings (Lb_t) (live weight, tonnes) were estimated using the fixed annual discarding rate (Dr_t) and estimated Cb_t (Eq 4.17). Annual discards (live weight, tonnes) were then estimated by subtracting Lb_t from Cb_t.

$$Lb_t = Cb_t(1 - Dr_t) \tag{4.17}$$

Estimated annual landings and discards were included in the likelihood function in the exact same manner as the age- and length- structured models, which resulted in the total variability in the catch (μ) and the fraction of this variability attributable to the landings (ζ) also being estimated parameters in this model.

Recruitment

Recruitment was defined as individuals large enough to be caught by either the commercial or survey gear. For king scallops in Cardigan Bay the lengths of typical recruits (~78 mm) roughly corresponded to individuals aged two years old (although large variation in the size of two-year olds exists). Due to limited understanding of the drivers of recruitment in scallop stocks, a stock recruit relationship was not used in the age- or length- structured models. Instead, the modelling of recruitment in both the age- and length- structured models involved estimating annual recruitment (number of king scallops) as annual estimated parameters (R_t), similar to Chen (2005), and then dividing these recruits in to classes. To reduce user bias in the estimation of each R_t, the median (R^{median}) and standard deviation (R^{sd}) of the prior distribution of R_t were estimated parameters in each of the age- and length- structured models.

For the length-structured model, the length distribution of the recruits was estimated with a log-normal distribution, as is common in length-structured models (Punt et al 2013), with the median length of recruits (l^R) and the standard deviation of recruit lengths (σ^R) estimated parameters in the model. The maximum length of recruits was also incorporated in the model to prevent recruits from being assigned to unrealistic length classes. Maximum length of recruits was a fixed parameter set as the maximum size of the small, yet distinct, peak at smaller length classes in each of the observed annual length-frequency distributions (Figure 4.12). The recruitment modelling approach implemented in this model meant the estimated length distribution of recruits did not vary annually.

In the length-structured model, the R_t estimates were multiplied by the recruit length distribution to assign recruits to the estimated stock. In contrast, the entire R_t estimates were assigned to age class two in the age-structured model. The unstructured model included recruitment as part of overall stock growth in Eq 4.6.

Estimated survey

Each model also evaluated estimated survey indices against observed survey indices. Estimated survey age-frequency (or length-frequency) distributions ($Ns_{a,t}$) were also included in the likelihood function for the age- and length-structured models. Survey data were not obtained in 2015, so survey data were not estimated in each model for this year. For the age- and length- structured models the survey equations were identical, and reference to length class (L) can be directly substituted for age class (a). In these two models the estimated survey data were calculated based on survey maximum absolute catch efficiency (q^V), age-structured survey (or length-structured) selectivity (s_a^V), the annual proportion of the assessment area swept by the survey each year (A_t) and the timing of the survey expressed as a fraction of the year (ρ_t). This resulted in survey abundance per age or length class, and the annual relative frequency of each class was calculated relative to the size of the annual total survey index. The annual total survey index was estimated as the summation of estimated numbers of scallops caught in the survey across age or length classes each year. As surveys were not conducted at the beginning of the year, the stock was updated appropriately based on the timing of the survey by incorporating growth, recruitment and mortality in to the survey equations to ensure consistency with the population dynamics and catch equations (Eq 4.18, 4.19 & 4.20). This meant that each of the three survey equations took in to account fishing which had taken place prior to the survey occurring in that year.

$$Ns_{a,t} = N_{a,t} s_a^v q^V A_t e^{-\frac{\rho_t * 12}{4}\left(\frac{1}{2}F_{a,t}+\frac{1}{3}M\right)} \; for \; 0 < \rho_t < \frac{1}{3} \tag{4.18}$$

$$Ns_{a,t} = ((N1_{a,t} P_a * \frac{(\rho_t * 12)-4}{6}) + (R_{a,t} * \frac{(\rho_t * 12)-4}{6}))e^{-\frac{(\rho_t * 12)-4}{6}\left(\frac{1}{2}M\right)} s_a^v q^V A_a \; for \; \frac{1}{3} < \rho_t < \frac{5}{6} \tag{4.19}$$

$$Ns_{a,t} = N2_{a,t} s_a^v q^V A_t e^{-\frac{(\rho_t * 12)-10}{2}\left(\frac{1}{2}F_{a,t}+\frac{1}{6}M\right)} \; for \; \frac{5}{6} < \rho_t < 1 \tag{4.20}$$

s_a^V was modelled as a logistic curve, as the survey gear were less likely to retain younger and smaller scallops (Eq 4.21). The shape (a_{10}^V or l_{10}^V) and scale (β^V, same name in each model) parameters of each curve were estimated parameters in both models. q^V was an estimated parameter in both models. A_t were calculated by, firstly, multiplying the length of each survey haul by the width of the mouth of a dredge and the number of dredges, to estimate the swept area for each survey haul. Secondly, the summation of the swept area of the hauls on each survey were then divided by the area of the assessment area to obtain A_t. A_t were then included as fixed parameters in each model. There were also two numerical constants in Eq 4.21 (ln(81) and ln(9)) which helped define the shape and position of the curve.

$$s_L^V = \frac{1}{1+e^{-\ln(81)\left(L-l_{10}^V\right)\frac{1}{\beta^V}+\ln(9)}} \tag{4.21}$$

The equations used to calculate the estimated survey indices in the unstructured model were also seasonal, reflecting the same three periods as the age- and length- structured models. In this model the estimated annual biomass of king scallops caught by the survey (Bs_t) was calculated based on stock size at the time of the survey (TSB_t, $TSB1_t$ or $TSB2_t$), absolute catch efficiency (q^V), the annual proportion of the assessment area swept by the survey each year (A_t) and the timing of the survey expressed as a fraction of the year (ρ_t) (Eq 4.22, 4.23 and 4.24).

$$Bs_t = q^V A_t \left(TSB_t - \left(\frac{\rho_t * 12}{4} * \frac{1}{2} q^F * TSB_t * E_t\right)\right) for \; 0 < \rho_t < \frac{1}{3} \tag{4.22}$$

$$Bs_t = q^V A_t \left(TSB1_t + \frac{(\rho_t * 12)-4}{6} * r * TSB1_t \left(1 - \frac{TSB1_t}{K}\right)\right) \; for \; \frac{1}{3} < \rho_t < \frac{5}{6} \tag{4.23}$$

$$Bs_t = q^V A_t \left(TSB2_t - \left(\frac{(\rho_t * 12) - 10}{2} * \frac{1}{2} q^F * TSB2_t * E_t \right) \right) \; for \; \frac{5}{6} < \rho_t < 1 \tag{4.24}$$

For each model the likelihood of the estimated survey indices were modelled against observed survey indices (Eq 4.25), with survey abundance (total count of scallops caught per annum) used in the age- and length- structured models and survey biomass (tonnes) of king scallops (total live weight caught per annum) used in the unstructured model. The CV for the survey indices (cv^V) (single value) was an estimated parameter in each model. In addition, both the age- and length- structured models evaluated the likelihood of estimated age- or length- distributions (Ns_{dist}^{est}) (Eq 4.26). Ns_{dist}^{est} was modelled with a Dirichlet-multinomial distribution, where *n* was the true sample size and α was a vector determining the mean and variance of the Dirichlet component of the distribution (Thorson et al 2017). The Dirichlet component of this distribution was incorporated to account for variation in age- or length- structure between individual survey hauls and overdispersion (Thorson et al 2017). To achieve this the Dirichlet component required a weighting parameter (*w*) which represented the effective sample size of the survey, and was an estimated parameter in each of the age- and length- structured models. The effective sample size accounted for non-independence of haul length or age or length compositions and (should have) weighted the survey compositional data appropriately against other data sources in each model (Thorson et al 2017). A full description of the Dirichlet-multinomial distribution and derivation of the weighting parameter can be found in Thorson et al (2017).

$$\ln Ns_{tot}^{obs} \sim Normal(\ln Ns_{tot}^{est}, \; (cv^V \ln Ns_{tot}^{est})^2) \tag{4.25}$$

$$Ns_{dist}^{obs} \sim Multinomial(Ns_{dist}^{est}, n) \; Dirichlet(Ns_{dist}^{est}, \; \alpha) \tag{4.26}$$

Model fitting

The joint likelihoods of the age- and length- structured models ($L(catch, index, dist|\theta)$) were defined as the product of the likelihoods of the catch (*catch*), survey index (*index*) and survey structure (age or length) distribution (*dist*), given the set of estimated parameters θ (Eq 4.27). The joint likelihood of the unstructured model ($L(catch, index|\theta)$) was defined as the product of the likelihoods of the catch (*catch*) and survey index (*index*), given the set of estimated parameters θ (Eq 4.28).

$$L(catch, index, dist|\theta) = L(catch|\theta) * L(index|\theta) * L(dist|\theta) \tag{4.27}$$

$$L(catch, index|\theta) = L(catch|\theta) * L(index|\theta) \tag{4.28}$$

In each model, the Hamiltonian Monte Carlo (HMC) method was used to estimate the joint posterior distribution of the estimated parameters which maximised the respective joint likelihood. The HMC method uses posterior gradient information to guide random sampling of the target posterior distribution, and this approach is a more efficient method for estimating the posterior distribution than the random walk implemented by the Markov Chain Monte Carlo (MCMC) sampling method (Neal 2011). Furthermore, the HMC method deals with the optimisation of the estimated parameters as a physical system as opposed to points in parameter space (Neal 2011). This allows the HMC method to explore the joint posterior distribution of the estimated parameters more effectively than other methods (Neal 2011). Betancourt (2017) provides a more detailed discussion on the geometric understanding of this method.

Each model was fitted using HMC implemented through Stan (Stan Development Team 2018). Each Stan model was implemented in R (R Core Team 2018) using the package 'rstan', which is the Stan interface for R. Stan automatically finds appropriate tuning parameters, such as number and size of sampling steps for exploring the joint posterior distribution, using a No-U-Turn Sampler (Hoffman and Gelman 2014). For each model, four sampling chains were initialised at different starting locations and for a number of iterations dependent on model. Warm up iterations (half the number of iterations) were discarded for each model, as these iterations were used to adjust the number and size of the sampling steps. Hunter (2015) found that 1,000 iterations were as effective as 10,000 for their variation of the length-structured model. However, 7,500 iterations were required for the length-structured model implemented here to provide reliable posterior estimates. The number of reliable posterior estimates were determined by the Stan software, which accounts for independence of samples from other samples and dependent samples are discarded for each estimated parameter. The age- and un- structured models used 2,000 iterations each as this number provided reliable posterior estimates and kept model run time low. Prior distributions were chosen for each of the estimated parameters in each model (length-structured = Table 4.2 (29 parameters), age-structured = Table 4.3 (27 parameters), unstructured = Table 4.4 (8 parameters)), so that realistic constraints were enforced on parameters and to avoid fitting unsuitable posterior distributions. The choice of prior distributions was based on a mixture of knowledge of parameter ranges and, for parameters which had some difficulty in statistical fitting, trial and error within sensible parameter ranges. Although the priors did not contain known information from other studies, this Bayesian approach was chosen to appropriately quantify the uncertainty associated with model estimates (McAllister and Ianelli 1997).

Table 4.2: Prior distributions given to the estimated parameters in the length-structured model.

Log-normal distributions parameterised and presented as median (first) and standard deviation (second) of underlying normal distribution. Normal and half-normal distributions parameterised and presented as median (first) and standard deviation (second). Beta distributions parameterised as two shape parameters.

Model Component	Parameter	Description	Units	Prior Distribution	Justification
Commercial fleet size-selectivity curve	l_{50}^{F}	Shape parameter	mm	Lognormal (ln(100), 0.4)	Centred at lower MLS (mm) with large enough standard deviation to allow a wide range of values.
	β^{F}	Scale parameter	mm	Lognormal(ln(40),1)	Centred at sensible selection range (mm) with and long tail allows for large values.
Commercial fleet discard ogive at size	l_{50}^{D}	Shape parameter	mm	Lognormal(ln(100),0.2)	Centred at lower MLS (mm) and lower standard deviation than $l_{50}^{F}$to ensure parameter remains close to MLS.
	β^{D}	Scale parameter	mm	Lognormal(ln(5),0.2)	Centred at narrow selection range (mm) to ensure steep discard selectivity curve.
Survey size-selectivity curve	l_{10}^{V}	Shape parameter	mm	Lognormal(ln(50),0.5)	Centred at sensible value based on observed survey data and with large standard deviation to allow sampling of wide range of values.
	β^{V}	Scale parameter	mm	Lognormal(ln(15),0.5)	Centred at reasonable selection range with standard deviation to allow sampling of wide range of values.

Survey catch efficiency	q^V	Maximum catch efficiency of king scallops	Proportion	Beta(1.5,1.5)	Symmetrical distribution constrained between 0 and 1.
Fishing mortality rate	$F_{t=1}$	Annual fishing mortality rate for initial year	Rate	Lognormal(ln(0.5),0.75)	Median set at 0.5 and wide standard deviation to sample range of values.
	F_t	Annual fishing mortality rate for years $t > 1$	Rate	Lognormal(ln(F_{t-1}),0.175)	Median set to fishing mortality from previous year and standard deviation low to allow for gradual changes in fishing mortality between years.
Recruitment	l^R	Median length of recruits.	mm	Lognormal(ln(78),0.3)	Centred at 78mm by visual inspection of survey length-frequency distributions. Standard deviation chosen to allow reasonable range of values.
	δ^R	Standard deviation of recruit lengths.	Unitless	Lognormal(ln(0.2),0.5)	Allows sensible range of recruit lengths when generating new recruits.
	R^{median}	Natural logarithm median number of recruits	Natural logarithm numbers	Normal(18,10)	Median value on log scale with very large standard deviation to allow sampling of wide range of values.
	R^{sd}	Standard deviation of number of recruits	Unitless	Halfnormal(0,0.5)	Sensible range and standard deviation to find suitable recruitment standard deviation
	R_t	Annual number of recruits	Numbers	Lognormal(Rmedian, Rsig)	Use model estimates of other priors to set median and standard deviation.
	R_{hist}	Annual historical number of recruits	Numbers	Lognormal(ln(250000),5)	Median value set to sensible guess for historical recruitment, with large standard deviation to allow sampling of a wide range of values.
Catch likelihood	μ	Variability	Unitless	Halfnormal(0,3)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values.
	ζ	Fraction of μ attributable to landings	Proportion	Beta(1.1,1.1)	Symmetrical distribution constrained between 0 and 1.
Survey likelihood	cv^V	Coefficient of variance in index	Unitless	Halfnormal(0,2)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values.
	w	Weighting parameter representing the effective sample size of size-frequency distributions	Unitless	Halfnormal(0,10)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values.

Model inspection and evaluation

For each model, correlation between estimated parameters and the mixing of the four chains were inspected (not presented here). The estimated parameter posterior distributions were compared to the respective prior distributions to inspect whether the specified prior distributions were having a large influence on the respective posterior distributions. Residual variation in the aggregated catch and aggregated survey data were calculated for all three of the models from observations (*Obs*) and estimates (*Est*) (Eq 4.29) and inspected for normality and temporal autocorrelation between each year (*t*) and the one prior. Standardised residual variation in the age- and length-frequency distributions were calculated and inspected for each of the age- and length- structured models, respectively (Eq 4.30), where *sd* was the standard deviation of the frequency distribution model estimates and *a* represented an age-class (or length-class). The standard deviation was calculated as the square root of the variance of the Dirichlet-multinomial distribution as reported in Thorson et al (2017) (Eq 4.31), where n_t was the relative number of samples each year and β_t was an annually estimated parameter from the Dirichlet-multinomial distribution representing overdispersion and was extracted from each model fit. Standardised residuals were preferred for the frequency distribution data as there these data had higher variation in residual magnitude caused by high variability in frequency distribution observations and estimates.

$$res_t = \ln \frac{Obs_t}{Est_t} \tag{4.29}$$

$$stdres_{t,a} = \frac{Obs_{t,a} - Est_{t,a}}{sd(Obs_{t,a})} \tag{4.30}$$

$$sd(Obs_{t,a}) = \sqrt{\frac{Obs_{t,a}(1 - Obs_{t,a})}{n_t}\left(\frac{n_t + \beta_t}{1 + \beta_t}\right)} \tag{4.31}$$

Model goodness-of-fit and comparison of goodness-of-fit between the three models was evaluated using plots of estimated data and observed data (presented in Results). Model goodness-of-fit and out-of-sample performance was not evaluated through information criteria methods as each model had a different joint-likelihood function which prevented comparison between models.

Estimation of TSB, SSB, MSY, B_{MSY}, carrying capacity, relative biomass and relative fishing mortality

The unstructured model estimated annual TSB directly, and SSB was not estimated by this model due to lack of stock structure to apply maturity information to. The unstructured model also estimated carrying capacity (*K*) directly and *MSY*, B_{MSY} and F_{MSY} were then estimated from the posterior distributions of the parameters *r* and *K* (Eq 4.32, 4.33 and 4.34) (Hilborn and Walters 1992).

$$MSY = \frac{rK}{4} \tag{4.32}$$

$$B_{MSY} = \frac{K}{2} \tag{4.33}$$

$$F_{MSY} = \frac{r}{2} \tag{4.34}$$

Table 4.3: Prior distributions given to estimated parameters in age-structured model.

Log-normal distributions parametrised and presented as median (first) and standard deviation (second) of underlying normal distribution. Normal and half-normal distributions parameterised and presented as median (first) and standard deviation (second). Beta distributions parameterised and presented as two shape parameters.

Model Component	Parameter	Description	Units	Prior Distribution	Justification
Commercial fleet age-selectivity curve	a_{50}^{F}	Shape parameter	Years	Lognormal (ln(3.5), 0.1)	Centred at age which roughly corresponds to lower MLS (mm) with low standard deviation to avoid sampling too far from this age.
	β^{F}	Scale parameter	Years	Lognormal(ln(1.25),0.2)	Centred at reasonable selection range (years) with low standard deviation to avoid sampling too far from this age.
Commercial fleet discard ogive at age	a_{50}^{D}	Shape parameter	Years	Lognormal(ln(3.25),0.1)	Centred at age similar which roughly corresponds to lower MLS (mm) and low standard deviation to ensure parameter remains close to MLS.
	β^{D}	Scale parameter	Years	Lognormal(ln(0.4),0.6)	Centred at narrow selection range (years) to ensure steep discard selectivity curve.
Survey age-selectivity curve	a_{10}^{V}	Shape parameter	Years	Lognormal(ln(1.1),0.1)	Centred at sensible value and low standard deviation to encourage sensible range of sampling.
	β^{V}	Scale parameter	Years	Lognormal(ln(1.75),0.2)	Centred at sensible selection range with standard deviation to allow sampling of sensible range of values.
Survey catch efficiency	q^{V}	Maximum catch efficiency of king scallops	Proportion	Beta(1.5,1.5)	Symmetrical distribution constrained between 0 and 1. Consistent with prior distribution of parameter from length-structured model.
Fishing mortality rate	$F_{t=1}$	Annual fishing mortality rate for initial year	Annual rate	Lognormal(ln(0.5),0.75)	Median set at 0.5 and wide standard deviation to sample range of values. Consistent with prior distribution from length-structured model.
	F_t	Annual fishing mortality rate for years $t > 1$	Annual rate	Lognormal(ln(F_{t-1}),0.175)	Median set to fishing mortality from previous year and standard deviation low to allow for gradual changes in fishing mortality between years. Consistent with prior distribution from length-structured model.
Recruitment	R^{median}	Natural logarithm median number of recruits	Natural logarithm numbers	Normal(18,10)	Median value on log scale, as this is a hyper-parameter, with very large standard deviation to allow sampling of wide range of values. Consistent with prior distribution from length-structured model.
	R^{sd}	Standard deviation of number of recruits	Unitless	Halfnormal(0,0.5)	Sensible range and standard deviation to find suitable recruitment standard deviation. Consistent with prior distribution from length-structured model.
	R_t	Annual number of recruits	Numbers	Lognormal(R^{median}, R^{sd})	Use model estimates of other priors to set median and standard deviation.

					Consistent with prior distribution from length-structured model.
	R_{hist}	Annual historical number of recruits	Numbers	Lognormal(ln(250 million),5)	Median value set to reasonable guess for historical recruitment, with large standard deviation to allow sampling of a wide range of values. Considerably large median required for this parameter than equivalent in length-structured model due to differences in recruitment modelling, and the recruits here will be spread through population over historical time.
Catch likelihood	μ	Variability	Unitless	Halfnormal(0,3)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values.. Consistent with prior distribution from length-structured model. Note observed catches vary considerably between years
	ζ	Fraction of μ attributable to landings	Proportion	Beta(1.1,1.1)	Symmetrical distribution constrained between 0 and 1. Consistent with prior distribution from length-structured model.
Survey likelihood	cv^V	Coefficient of variance in index	Unitless	Halfnormal(0,2)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values. Consistent with prior distribution from length-structured model.
	w	Weighting parameter representing the effective sample size of age-frequency distributions	Unitless	Halfnormal(0,10)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values. Consistent with prior distribution from length-structured model.

To estimate annual TSB in the age- and length- structured models annual age- or length- structured abundance was converted to biomass (live weight, tonnes) by multiplication with mean weight-at-age or weight-at-length. To estimate annual SSB, mature scallop biomass for each age or length was estimated as the product of the biomass in each age or length class and the fraction of mature individuals per class. The fractions of mature individuals -at-age and -at-length were determined by fitting logistic curves (Eq 4.9) to the proportion of mature individuals at each age- or length- class from the sample of 472 laboratory dissected king scallops, prior to main model fitting. The shape and scale parameters of each curve were estimated using a nonlinear least squares model. Annual TSB and SSB were then obtained by summation of age- or length- structured biomass and mature biomass across classes, respectively.

Estimation of MSY, B_{MSY}, F_{MSY} and carrying capacity for the age- and length- structured models was conducted by fitting an unstructured model to the annual median TSB estimates, and their 95% prediction intervals, from each of these two models. The unstructured model used for this was simpler than the primary unstructured model being compared to the age- and length- structured models in this study and re-estimated TSB (B_t) for each year in the time series so that the parameters r and K could be estimated (Eq 4.35). Instead of estimating catches using observed effort and fleet catchability, the observed landings (Lb_t^{obs}) were directly included to reduce the number of estimated parameters. The estimated TSB was modelled against observed TSB (in this case observed TSB were the TSB estimates from each of the age- and length- structured models) with a likelihood function (Eq 4.36).

Table 4.4: Prior distributions given to estimated parameters in primary unstructured model.

Log-normal distributions parameterised and presented as median (first) and standard deviation (second) of underlying normal distribution. Normal and half-normal distributions parameterised and presented as median (first) and standard deviation (second). Beta distributions parameterised and presented as two shape parameters.

Model Component	Parameter	Description	Units	Prior Distribution	Justification
Stock size	$TSB_{hist=1}$	TSB of historical stock in year 1 (historical time)	Live weight, tonnes	Lognormal (ln(5000), 1)	Centred at sensible value with large standard variation to permit sampling of wide range of values.
	K	Carrying capacity of stock	Live weight, tonnes	Lognormal(ln(10000),1)	Centred at sensible value with large standard variation to permit sampling of wide range of values.
	r	Intrinsic stock growth rate	Rate	Lognormal(ln(0.8),1)	Centred at sensible value with large standard variation to permit sampling of wide range of values.
Catch	q^F	Fleet catchability	Unit less	Beta(0.2,1.5)	Centred at low value to encourage sampling of low values.
Survey	q^V	Maximum catch efficiency of king scallops	Proportion	Beta(1.5,1.5)	Symmetrical distribution constrained between 0 and 1. Consistent with prior distribution of parameter in both length- and age-structured models.
Catch likelihood	μ	Variability	Unit less	Halfnormal(0,3)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values. Consistent with prior distribution of parameter in both length- and age-structured models.
	ζ	Fraction of μ attributable to landings	Proportion	Beta(1.1,1.1)	Symmetrical distribution constrained between 0 and 1. Consistent with prior distribution of parameter in both length- and age-structured models.
Survey likelihood	cv^V	Coefficient of variance in index	Unit less	Halfnormal(0,2)	Halfnormal distribution permits large values, and large standard deviations allows wide range of sample values. Consistent with prior distribution of parameter in both length- and age-structured models.

$$B_{t+1} = B_t + rB_t\left(1 - \frac{B_t}{K}\right) - Lb_t^{obs} \tag{4.35}$$

$$\ln B_{tot}^{obs} \sim Normal(\ln B_{tot}^{est},\ (cv^B \ln B_{tot}^{est})^2) \tag{4.36}$$

This approach was taken as other approaches for estimating MSY rely on the existence of a stock-recruit relationship (Hilborn and Walters 1992) or a relationship between TSB and surplus production (Jacobsen 2002), neither of which existed over the short time series. Surplus production is the difference between production (stock growth) and those removed by natural mortality (stock decline), and therefore represents the size of catch that may be fished to maintain a constant stock size (Hilborn and Walters 1992). The intrinsic population growth rate (*r*), carrying capacity (*K*), initial TSB (B_1) and coefficient of variation of TSB (cv^B) were estimated parameters in each of the unstructured models applied to the age- and length- structured TSB estimates. These models were fitted using HMC sampling with Stan, and executed through R as detailed for the main models. Similarly, four sampling chains were executed per model with 2,000 iterations per chain. Prior distributions were chosen for each of the estimated parameters in each model (length-structured unstructured fit = Table 4.5, age-structured unstructured fit = Table 4.6) (each 4 parameters).

Table 4.5: Prior distributions given to estimated parameters in the simple unstructured model fitted to length-structured TSB estimates.

Log-normal distributions parameterised and presented as median (first) and standard deviation (second) of underlying normal distribution. Half-normal distributions parameterised and presented as median (first) and standard deviation (second).

Model Component	Parameter	Description	Units	Prior Distribution	Justification
Stock size	$B_{t=1}$	TSB in year 1 of time series (tonnes).	Live weight, tonnes	Lognormal (ln(3725), 1)	Centred at value of median 'observed' biomass in year 1 from length-structured model. Large variance to allow sampling of range of values.
	K	Carrying capacity of stock.	Live weight, tonnes	Lognormal(ln(15000),1)	Centred at sensible value with large variance to allow range of sampling values.
	r	Intrinsic stock growth rate.	Rate	Lognormal(ln(0.8),1)	Centred at sensible value with large variance to allow sampling of range of vales.
Stock size likelihood	cv^B	Coefficient of variation of TSB.	Unit less	Halfnormal(0, 2)	Halfnormal distributions permits large values, and large standard deviations allows wide range of sample values.

Relative biomass, calculated as estimated annual TSB divided by estimated B_{MSY}, and relative fishing mortality rate, calculated as estimated annual fishing mortality rate divided estimated F_{MSY}, were also estimated for each model. The annual fishing mortality rate from the unstructured model was estimated as the product of observed annual effort (E_t) and estimated fleet catchability (q^F).

Sensitivity analysis of natural mortality rate

A sensitivity analysis of the fixed annual natural mortality rate, *M*, was conducted for each of the age- and length-structured models across the range of values 0.1, 0.15, 0.2, 0.25 and 0.3 yr^{-1}. These values were selected as they were regularly spaced across a range which included the majority of natural mortality rates that have been reported for other scallop fisheries, or used in other scallop stock assessments (Table 1.5). Although a natural mortality rate of 0.5 yr^{-1} was used in a New Zealand scallop fishery stock assessment, this valued was considered too high for a king scallop stock and therefore the range used here was capped at 0.3 yr^{-1}.This range was also the same range used in a similar sensitivity analysis conducted for the Isle of Man king scallop fishery (Allison 1993). Each model was fitted with each of the values of *M*, to produce five sets of results for each model corresponding to the five values of *M*. All other fixed parameters and estimated parameter prior distributions were kept identical, however the number of model iterations per chain was increased (as guided by the software) for some values of *M* to avoid estimated parameter confounding and to produce reliable posterior estimates. The results of the sensitivity analysis of *M* are presented as a graphical comparison of median posterior estimates of key model outputs (annual fishing mortality rate, stock size and recruitment) and percentage changes in median and CV of samples when changing *M*.

Table 4.6: Prior distributions given to estimated parameters in the simple unstructured model fitted to age-structured TSB estimates.

Log-normal distributions parameterised and presented as median (first) and standard deviation (second) of underlying normal distribution. Half-normal distributions parameterised and presented as median and standard deviation.

Model Component	Parameter	Description	Units	Prior Distribution	Justification
Stock size	$B_{t=1}$	TSB in year 1 of time series	Live weight, tonnes	Lognormal (ln(4634), 1)	Centred at value of median 'observed' biomass in year 1 from length-structured model. Large variance to allow sampling of range of values.
	K	Carrying capacity of stock	Live weight, tonnes	Lognormal(ln(8000),1)	Centred at reasonable value with large variance to allow range of sampling values.
	r	Intrinsic stock growth rate.	Rate	Lognormal(ln(0.2),1)	Centred at reasonable value with large variance to allow sampling of range of vales.
Stock size likelihood	cv^B	Coefficient of variation of TSB	Unit less	Halfnormal(0, 2)	Halfnormal distributions permits large values, and large standard deviations allows wide range of sample values.

Sensitivity of *M* within each model type was also evaluated by comparing the out-of-sampling performance, expressed as the Widely Applicable Information Criterion (WAIC). This information criterion makes no assumption about the shape of the joint posterior distribution and was calculated from the joint log-posterior-predictive density (lppd) and a penalty term, which incorporates both the joint posterior ($p(y_i|\vartheta)$), where y_i is an observation and ϑ the joint posterior samples, and variance of the joint posterior samples (var_ϑ) (Eq 4.37) (McElreath 2020).

$$WAIC(y,\vartheta) = -2\left(lppd - \textstyle\sum_i var_\vartheta \log\left(p(y_i|\vartheta)\right)\right) \tag{4.37}$$

The final model results presented used an *M* value which was selected by interpretation of the sensitivity results and knowledge of natural mortality rates used in other king scallop stock assessments. The final selection of *M* is described in the *Results* section after consideration of the sensitivity results.

4.3 Results

Survey results

The survey swept 0.019, 0.022, 0.026 and 0.037 km^2 of seabed in 2012, 2013, 2014 and 2016 respectively, which corresponded to between 0.001 and 0.004 % of the assessment area being swept each year (assessment area was 1,372 km^2). The survey indices (number of king scallops caught per 100m^2 of seabed swept) ranged from 0 to 10.5 (Figure 4.3). The 2013 survey had hauls with the highest densities, and the 2016 survey had the most hauls with low densities. The total biomass (live weight) of king scallops obtained on each of these surveys was 0.062, 0.094, 0.066 and 0.033 tonnes in 2012, 2013, 2014 and 2016 respectively.

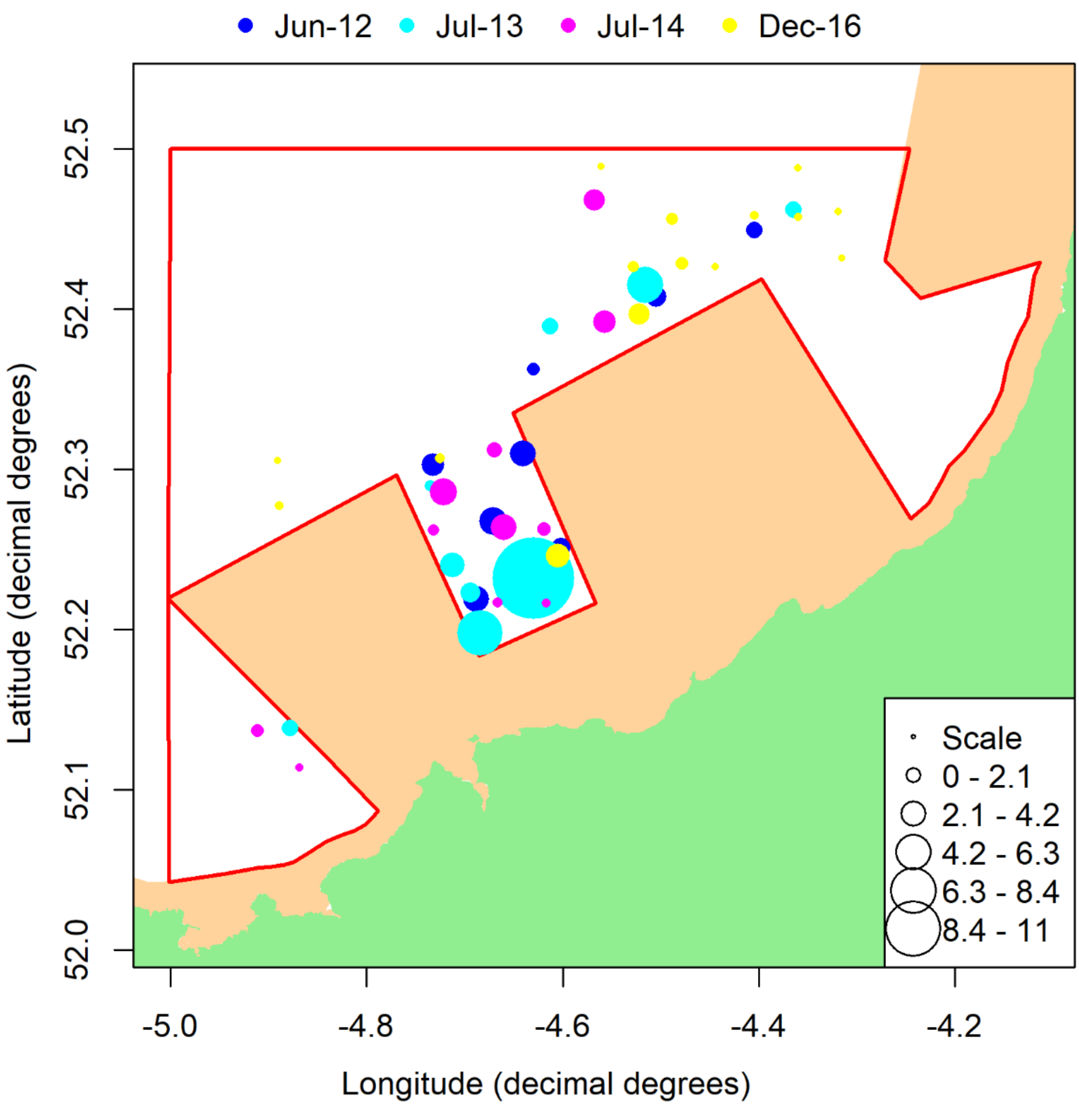


Figure 4.3: A map of the survey indices coloured by annual survey. Red outline is the assessment area, and all white area within is sea open to commercial scallop dredging. The orange areas are areas of sea closed to commercial scallop dredging and green is land. Each point represents a survey haul and is scaled in size relative to density of king scallops caught (number caught per 100m² of seabed swept).

Sensitivity analysis of natural mortality rate

Increasing the annual natural mortality rate resulted in a decrease in estimated median annual fishing mortality rate for each year in the time series and an increase in estimated median total stock abundance, median TSB and median recruitment in each year, for each of the length- and age-structured models (Figure 4.4 and Figure 4.5). The only exceptions were where higher values of *M* resulted in a lower estimate of median total stock abundance and median TSB for the years 2015 and 2016 in the age-structured model, compared with lower values of *M*. Despite the change in estimated median magnitudes, there were only minor changes in the estimated trends with time for these metrics in the length-structured model and fishing mortality rate and recruitment in the age-structured model. The effect of an increase of natural mortality rate on the estimated trend with time of median total stock abundance and median TSB was more complex in the age-structured model, and evidently was affected by choice of natural mortality rate.

Changing *M* from 0.15 to 0.2 caused the greatest absolute percentage change (more negative in this case) in estimated median annual fishing mortality rate for each year in the time series and changing M from 0.1 to 0.15 caused the least absolute percentage change (negative), in the length-structured model (Figure 4.6, Row 1, Column 1). Conversely, changing *M* from 0.15 to 0.2 caused the least absolute percentage change (negative) in estimated median annual fishing mortality rate for each year in the time series in the age-structured model (Figure 4.6, Row 1, Column 1). The other changes represented medium percentage changes in estimated median annual fishing mortality rate (all negative). There was a trend with time for the greatest absolute percentage change (negative) to occur in 2016 for the majority of changes in *M* across both models. The absolute percentage change in estimated fishing mortality rate for the length-structured model was always greater (more negative) than the age-structured equivalents.

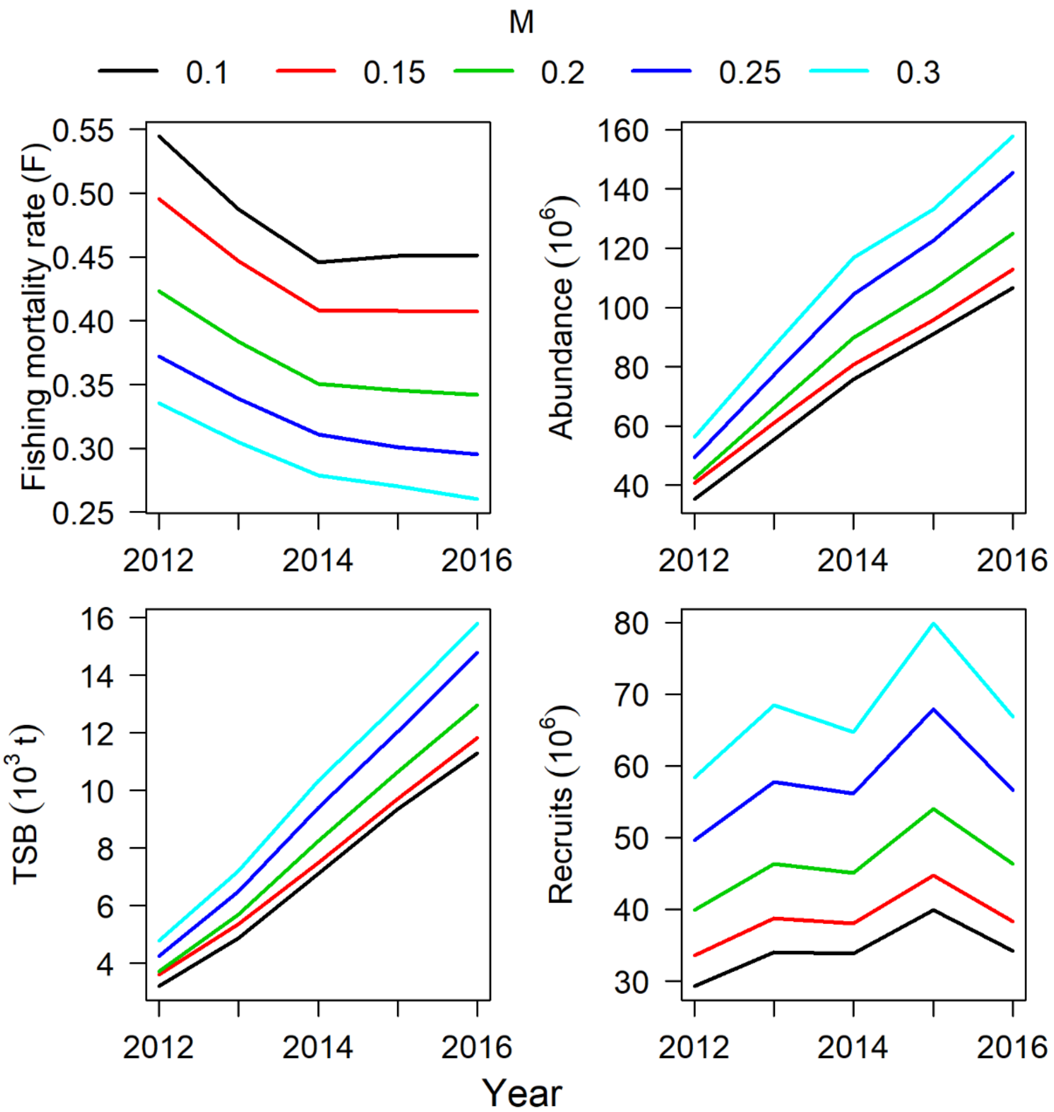


Figure 4.4: Median estimates of annual fishing mortality rate (averaged across scallops > 110 mm shell width), total stock abundance (millions of scallops), total stock biomass (TSB) (thousands of tonnes) and recruits (millions) from the length-structured model from five model tests each using a different value of natural mortality rate (M).

Changing *M* from 0.2 to 0.25 caused the greatest percentage change (positive) in each of median total stock abundance, TSB and recruitment for all years (except recruitment in 2016) for the length-structured model (Figure 4.6, Row 1, Columns 2 - 4). Changing *M* from 0.1 to 0.15 caused the least percentage change in recruitment for all years in the length-structured model (Figure 4.6, Row 1, Columns 2 - 4). There was little evidence of a trend between median percentage change and time across these three metrics as *M* was changed for the length-structured model. Changing *M* from 0.1 to 0.15 caused the greatest absolute percentage change (positive) in each of median total stock abundance, TSB and recruitment in the age-structured model, however towards the end of the time series the absolute percentage change from 0.15 to 0.2 was greater for median total stock abundance and TSB (Figure 4.6, Row 1, Columns 2 – 3). Generally, the median percentage change decreased with time for each of the median total stock abundance, TSB and recruitment in the age-structured model but this resulted in an increase in absolute percentage change after 2015 (as the lines pass through 0 and became more negative) (Figure 4.6, Row 1, Columns 2 - 4). In many cases the absolute percentage change of the medians of these metrics were lower in the age-structured model than the respective percentage changes in the length-structured model.

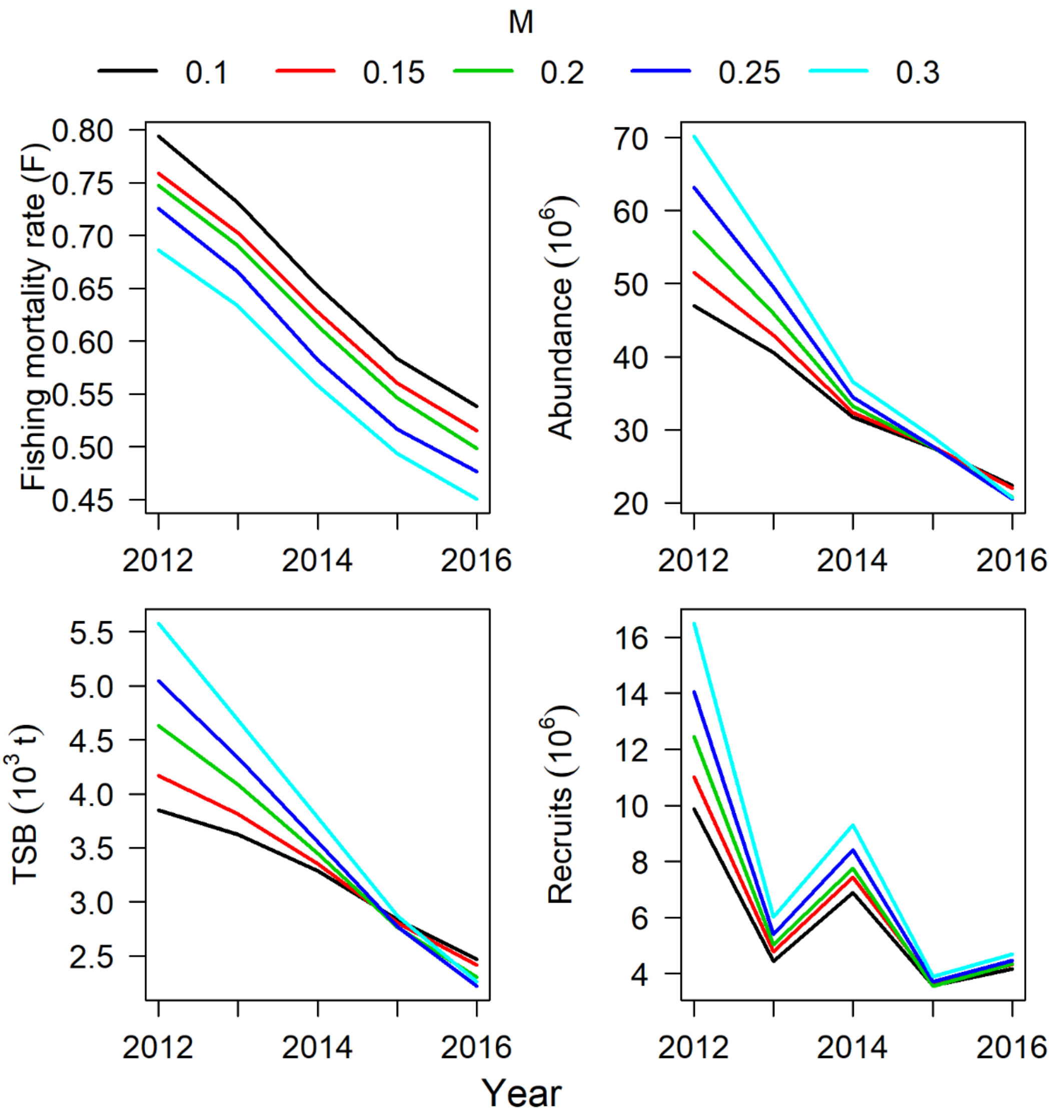


Figure 4.5: Median estimates of annual fishing mortality rate (averaged across scallops > 110 mm shell width), total stock abundance (millions of scallops), total stock biomass (TSB) (thousands of tonnes) and recruits (millions) from the age-structured model from five model tests each using a different value of natural mortality rate (M).

Changing *M* from 0.1 to 0.15 and 0.15 to 0.2 caused the greatest percentage change in the CV of estimated annual fishing mortality rates for the length-structured model, although these changes were in opposite directions (increase and decrease from previously values, respectively) (Figure 4.6, Row 2, Column 1). The percentage change in the CV of estimated annual fishing mortality rates from the age-structured model was less than the length-structured model for the majority of years for each change in *M,* with the change in *M* from 0.25 to 0.3 causing the greatest percentage change in CV (Figure 4.6, Row 2, Column 1). The percentage change in the CV of the estimated annual fishing mortality rates did not follow a consistent trend with time for either model.

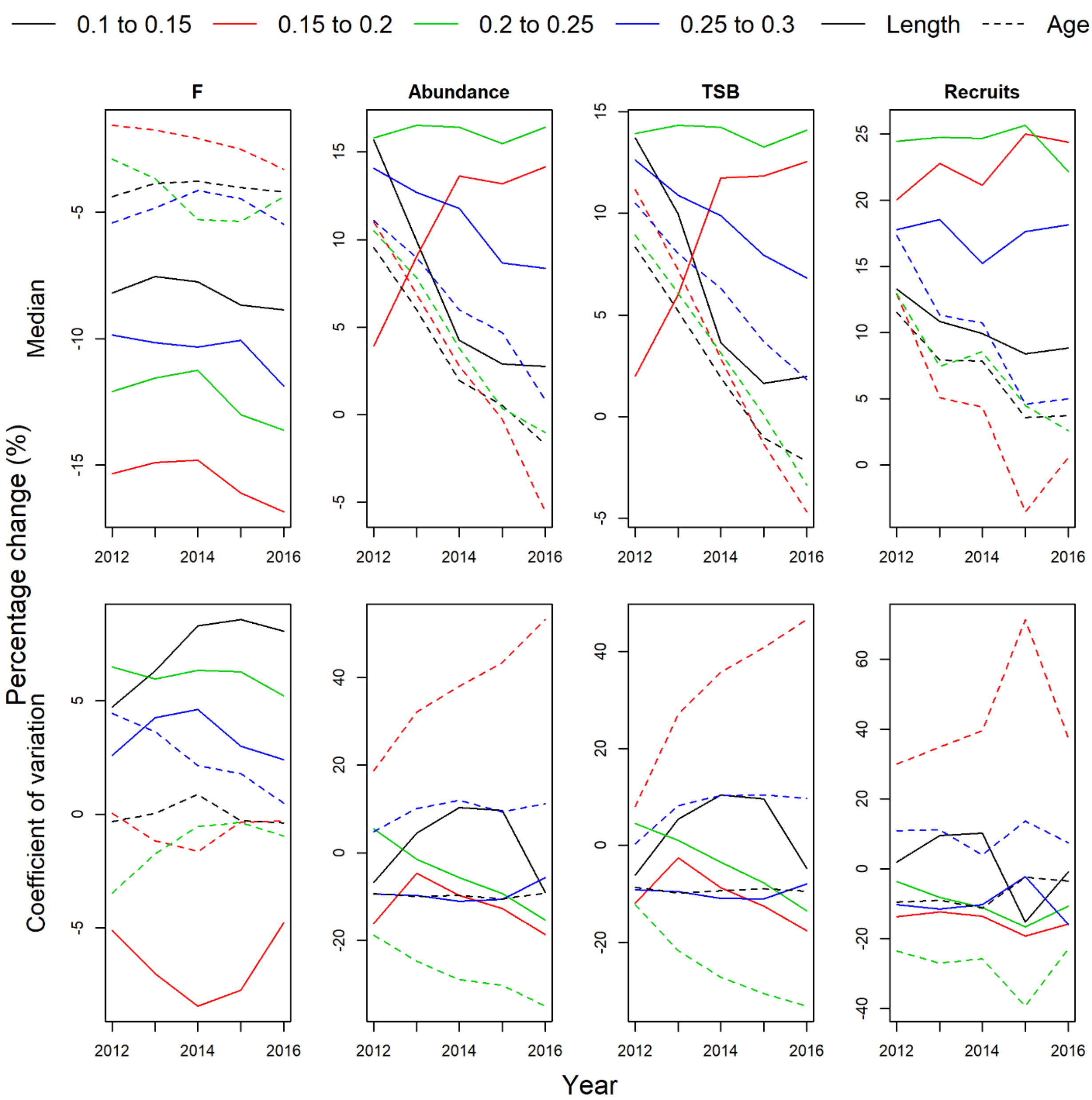


Figure 4.6: Change in percentage of median and coefficient of variation with time for each of estimated annual fishing mortality rate (averaged across scallops > 110mm shell width) (F), total stock abundance, total stock biomass (TSB) and recruitment estimates for each of the length- and age-structured models as the annual natural mortality rate (M) is incremented by 0.05. Change from one value of M to another is indicated by colour as described in the plot legend. Change was calculated from the median or coefficient of variation estimated with the value of M listed first to the median or coefficient of variation estimated with the value of M listed second, and calculated by: $\%\ change = \frac{second - first}{first} * 100$ *. The length-structured model results are denoted with undashed lines, and age-structure model results with dashed lines.*

Changing *M* from 0.15 to 0.2 caused the greatest absolute percentage change (positive) in the CV of each of estimated total stock abundance, TSB and recruitment in the age-structured model (Figure 4.6, Row 2, Columns 2-4). Changing *M* from 0.2 to 0.25 also caused a large absolute percentage change in CV for all estimated metrics in each year for this model, however each change was a decrease from the previous values of *M*. The percentage changes in these estimated metrics for these changes in *M* were much larger than any percentage changes in CV caused by changing *M* in the length-structured model (Figure 4.6, Row 2, Columns 2-4). There was no trend of percentage change in CV with time for either of the models.

The lowest WAIC value was found when M = 0.3 in each of the age- and length- structured models, and highest when M = 0.1 or 0.15 (Table 4.7). Therefore, model tests using M = 0.3 indicated a greater out-of-sample performance (as measured by WAIC) and, generally, a narrower spread of sampled estimates compared to the other values of M that were tested across both models. However, further testing of the model, not displayed here, indicated that the WAIC kept on decreasing with increasing increments of 0.05 of M for each model. Therefore, the WAIC was not particularly informative as it favoured ever increasing values of M.

As a result of the WAIC values proving unreliable, the natural mortality rate selected for the age- and length- structured models was based on the value used in other king scallop stock assessment models (M = 0.15, Allison 1993; Dobby et al 2017). However, when this value was tested in the length-structured model considerable model fitting issues occurred (namely high correlation between estimated parameters) and the lowest WAIC was produced (despite not being the lowest M value tested). Furthermore, large percentage changes in median and CV of key estimates were observed when changing to or from this value of M, indicating unusual key output estimates were made by each of the age- and length-structured models when M = 0.15. Therefore, a value of M = 0.2 was used as this was the closest value to 0.15 tested which had a lower WAIC value across both models.

Table 4.7: Widely Applicable Information Criterion (WAIC) values for each value of natural mortality rate (M) used in the sensitivity tests of the age- and length- structured models.

	WAIC value	
Natural mortality rate (yr^{-1}) (M)	Length-structured model	Age-structured model
0.1	13825.1	5076.9
0.15	13825.7	5075.2
0.2	13818.9	5072.9
0.25	13817.8	5071.2
0.3	13814.7	5070.9

Parameter estimates

The posterior distributions of each of the estimated parameters are reported for the length-structured model (Figure 4.7), the age-structured model (Figure 4.8) and the primary unstructured model compared here (Figure 4.9). The relative frequency, or density, of parameter values in each posterior distribution reflects the rate of change in cumulative probability of each sampled value being the true value. A low relative frequency indicates a value is more unlikely for a given parameter, whereas a high relative frequency indicates a value is more likely. The value of the highest relative frequency estimates for each parameter were all sensible. Key estimated parameters are reported further in forthcoming subsections.

These figures can also be used to assess the influence of prior distributions on the respective posterior distributions of each estimated parameter. Several of the posterior distributions of the age- and length- structured model were strongly driven by their prior distributions. These included β^D(the scale parameter of the discard curve), cv^V (coefficient of variation of the survey index) and some of the annual recruit and fishing mortality rate parameters. A posterior distribution which is strongly driven by the prior distribution means the parameter is being driven by the user (through prior distribution choice) rather than by data. The posterior distributions of other parameters, for example the R_{hist} and ζ parameters, were reasonably independent of their prior distributions. The majority of the posterior distributions of parameters in the unstructured model were reasonably independent of their prior distributions, with the exception of cv^V.

The natural mortality estimate used in both the age- and length- structured models was 0.2 yr^{-1}, as outlined previously. The fixed von Bertalanffy growth parameters estimated for the length-structured model were L_∞= 139.6 mm and k = 0.375. The length-weight relationship fixed parameters estimated for the length-structured model were a = 0.0000005 and b = 2.695. The age-weight relationship fixed parameters estimated for the age-structured model were x = -0.128 and y = 0.136. The curves produced from these three sets of parameters are presented in Figure 4.10.

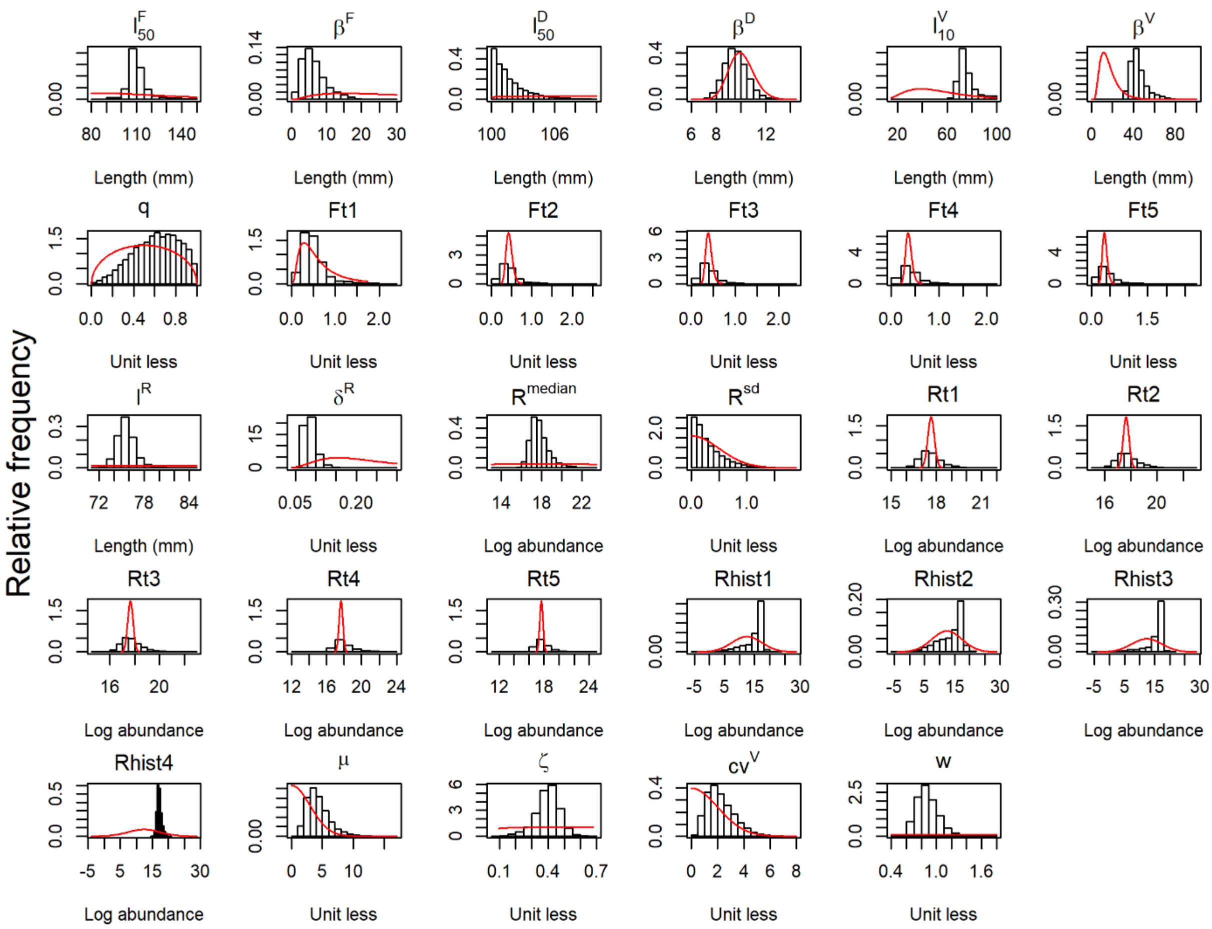


Figure 4.7: Prior and posterior distributions for each of the estimated parameters in the length-structured model. On each panel the bars are the posterior distribution and the red curve is the prior distribution. The y-axis is the relative frequency of each parameter value from model sampling and the x-axis is on the scale of each parameter value.

Model fits to observed data

The model estimates of annual landings, discards, catch and total survey indices showed varying degrees of goodness-of-fit to the respective observed data across each of the models (Figure 4.11). The observed data fell within the 95% prediction intervals (PIs) of the estimated data for the majority of years for all four of the age-structured model panels, with the exceptions being the landings and catch in 2015, the landings, discards and catch in 2016 and the survey index in 2013 (Figure 4.11, Column 2). In addition, each of these estimated metrics followed the decreasing trend with time in the observed data for the age-structured model. The observed landings, discards and catches fell outside the 95% PIs of the estimated data in the years 2015 and 2016 for the length-structured model (Figure 4.11, Rows 1- 3, Column 1). The observed survey index only fell within the 95% PIs of the estimated data in 2014 for the length-structured model (Figure 4.11, Row 4, Column 1). In addition, each of these estimated metrics failed to follow the decreasing trend with time in the observed data for the length-structured model.

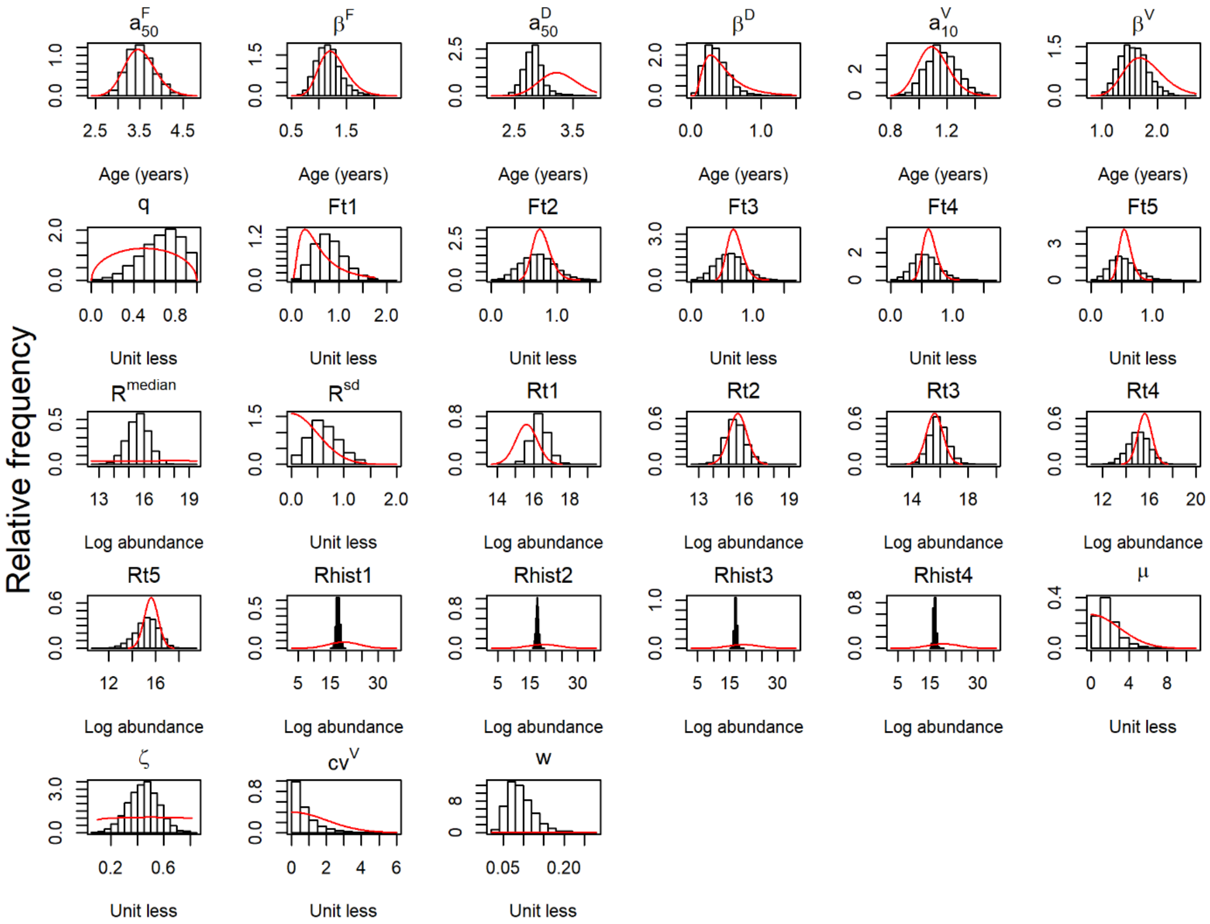


Figure 4.8: Prior and posterior distributions for each of the estimated parameters in the age-structured model. On each panel the bars are the posterior distribution and the red curve is the prior distribution. The y-axis is the relative frequency of each parameter value from model sampling and the x-axis is on the scale of each parameter value.

The majority of the observed data for the landings, discards, catch and survey indices fell within the PIs of the respective data in each year for the unstructured model, apart from the landings, discards and catch in 2014 and the survey index in 2013 and 2016 which all fell marginally outside (Figure 4.11, Rows 1-4, Column 3). The estimated landings, discards and catch followed the decreasing trend with time in the observed data, however the estimated survey indices failed to follow this trend.

The estimated survey length-frequency distribution captured the variability in the observed survey length-frequency distributions reasonably well across all years, with under- and over- estimations as expected with such fine classes (Figure 4.12). The estimations captured the recruits in the survey, which are the peak that can be observed in the smaller length classes of every year. The best model estimations of length-frequency were for the years 2012 and 2013, where in 2014 and 2016 the estimations did not capture all the variability in the observed data. The estimated survey age-frequency distribution from the age-structured model captured the variability in the observed survey age-frequency distributions reasonably well across all years (Figure 4.12). The estimated data captured the peak age-class in each year, although the estimated data continually underestimated the relative frequency of this peak age-class. The relative frequency of other age classes were overestimated in each year.

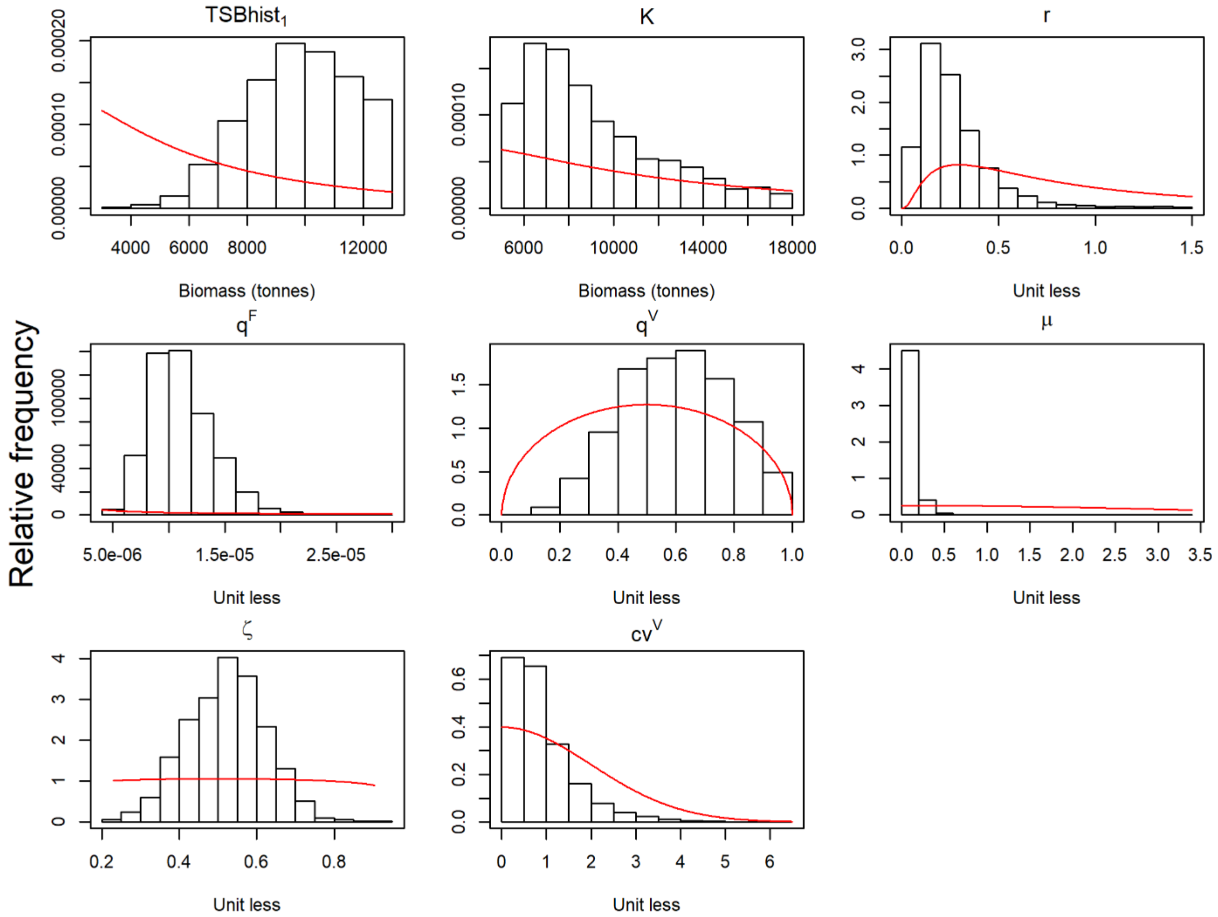


Figure 4.9: Prior and posterior distributions for each of the estimated parameters in the primary unstructured model. On each panel the bars are the posterior distribution and the red curve is the prior distribution. The y-axis is the relative frequency of each parameter value from model sampling and the x-axis is on the scale of each parameter value.

The residuals of the catch were fairly well distributed around the quantile-quantile (qq) line for the length-structured model (Figure 4.13, Row 1, Column 1), indicating the observed and estimated data were of similar distribution. The residuals of the catch were less well distributed around the qq line for the age- and un-structured models, indicating differences in the observed and estimated data distributions (Figure 4.13, Row 1, Columns 2 & 3). There was no evidence of temporal correlation between catch residuals for any of the models (Figure 4.13, Row 2, Columns 1, 2 & 3) (note that correlation of 1 is expected for the initial residual). The residuals of the total survey indices were not well distributed in any of the models, indicating differences in the observed and estimated data distributions (Figure 4.13, Row 3, Columns

1, 2 & 3). There was no evidence of temporal correlation between survey index residuals for either of the three models (Figure 4.13, Row 4, Columns 1, 2 & 3).

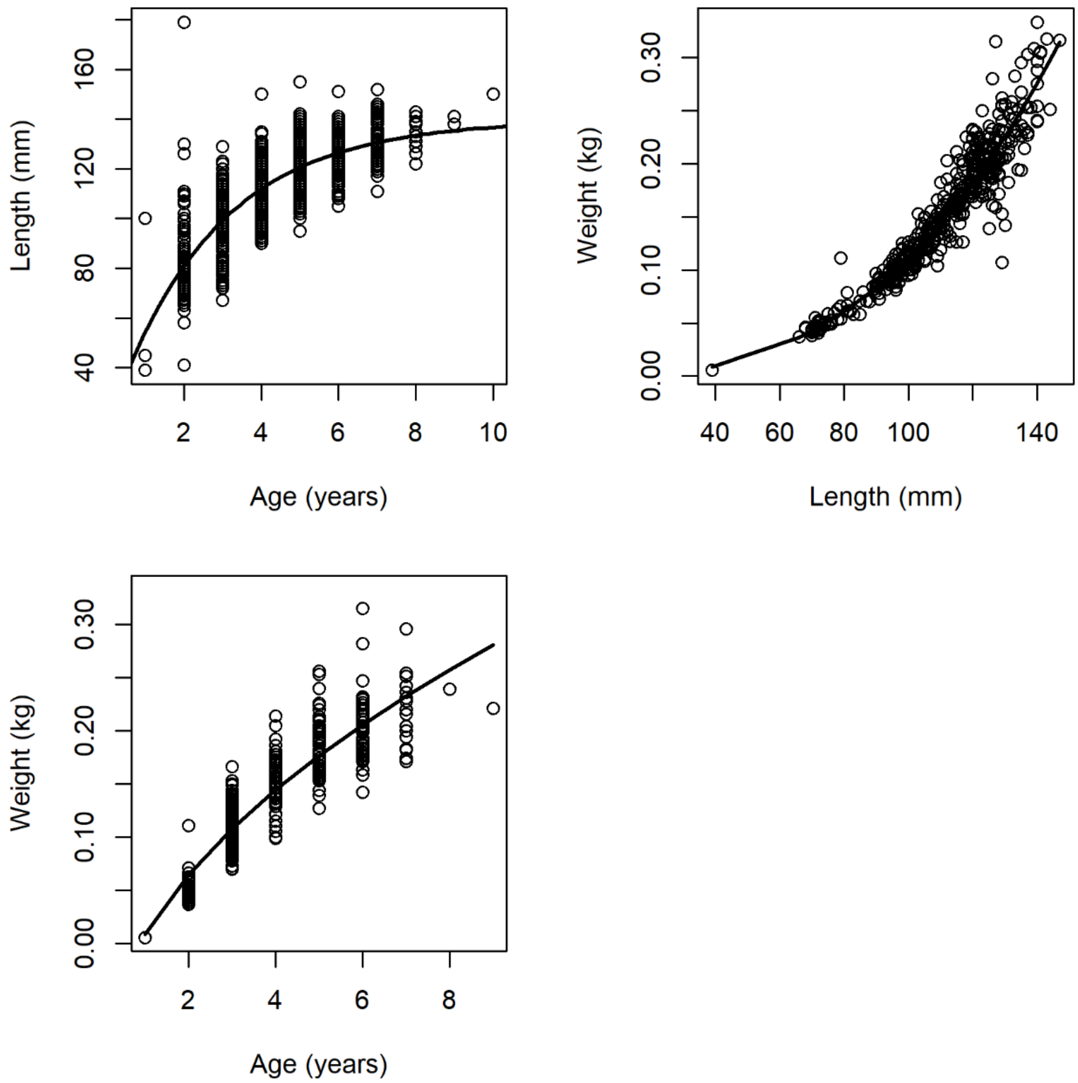


Figure 4.10: Three panels showing stock structure relationships. Top left is length-at-age and was fitted with a von Bertalanffy growth equation, where length is shell width (mm) and age is measured in years. Top right is weight-at-length and was fitted with an allometric growth power equation, where weight is live weight (kg). Bottom left is weight-at-age and was fitted with a square root equation.

The age- and length-structured standardised residuals indicated some issues in model fitting to the structured survey data (Figure 4.14). A relatively high, positive standardised residual existed for age six in 2012, indicating that the observation was much greater than expected relative to the model standard deviation in age frequency distributions. Similarly, although to a far lower magnitude, a relatively high, positive standardised residual existed for length-classes 41 mm in 2012 and 51 mm in 2016. The remainder of length- and age-class standardised residuals were relatively low for all years.Figure 1.3

Model estimates of key stock parameters

Each of the length- and age-structured models estimated the shape and scale parameters for three selectivity curves (Figure 4.15). Median fishery selectivity rapidly increased for king scallops greater than 100 mm shell width in the length-structured fishing selectivity curve, and median full selectivity occurred at approximately 110 mm. The PIs were relatively wide, indicating a reasonable degree of uncertainty in this curve. The fishery retention fraction rapidly increased between 90 mm and 110 mm and PIs were narrower than the fishing selectivity curve. The survey selectivity curve, which has been multiplied by q^V and therefore represented the absolute catch efficiency of the survey gear, rapidly increased between 70 mm and 100 mm shell width, and the width of the PIs increased with increasing king scallop shell width (i.e. length). For the age-structured curves, it is important to consider that the younger age classes contain a greater range of shell widths than older age classes and therefore the shape of these curves are expected to differ from the length-structured equivalents. The mean age-structured fishing selectivity increased after age two and median full selectivity occurred at approximately age five. The PIs were relatively narrow. The age-structured median fishery retention fraction rapidly increased after age two, mean full retention occurred at age four, and the PIs were also reasonably narrow. The age-structured median survey selectivity, again representing absolute catch efficiency, increased from age one to age four, after which catch efficiency remained constant with increasing age. The PIs were wide for estimated catch efficiency of king scallops aged four and older.

The estimated fishing mortality rate (averaged across scallops of shell width > 110mm) decreased with time in each of the length- and age-structured models, with estimates higher in the age-structured model for each year (Figure 4.16, Row 1, Columns 1-2). Fishing mortality rate decreased more rapidly with time in the unstructured model, and the PIs were narrower than the other two models (Figure 4.16, Row 1, Column 3). The median estimated fishing mortality rate was very similar between the length- and un-structured models at the beginning of the time series. Fishing mortality rate was validated by comparison to observed effort from the area, where fishing mortality rate is assumed to be an invariant measure of effort. Observed effort (thousand hours fished) from the assessment area decreased more rapidly with time than any of the model estimated fishing mortality rates.

The total stock abundance was estimated to be increasing with time in the length-structured model, and decreasing with time in the age-structured model (Figure 4.16, Row 2, Columns 1-2). The PIs were considerably larger in the length-structured model. Likewise, the TSB increased with time in the length-structured model, and decreased with time in both the age- and un-structured models (Figure 4.16, Row 3, Columns 1-3). The PIs were largest in the length-structured model, and the smallest in the unstructured model. SSB followed the same respective trends in the length- and age-structured models (Figure 4.16, Row 4, Columns 1-2). The number of recruits fluctuated throughout the time series in both the length- and age-structured models, with increases and decreases observed and greater PIs in the length-structured model (Figure 4.16, Row 4, Columns 1-2).

TSB was expressed as densities and compared across models (Figure 4.17). The densities for each model were multiplied by the estimated maximum survey catch efficiency (q^V) to compare with observed survey estimates. As this approach was approximate, this was only conducted to determine whether TSB estimates were on an appropriate scale rather than looking for precise overlap. Both the median density estimates, scaled by q^V, from the length- and age-structured models were similar to the observed survey densities in 2012, and the length-structured model was again similar in 2013. For consequent years the median length-structured densities became greater than the observed survey densities. The median age-structured densities were less than the observed survey densities in 2013 and 2014, but greater in 2016. The median unstructured model density estimates were higher than the observed survey densities in 2012, lower in 2013, similar in 2014 and higher in 2016.

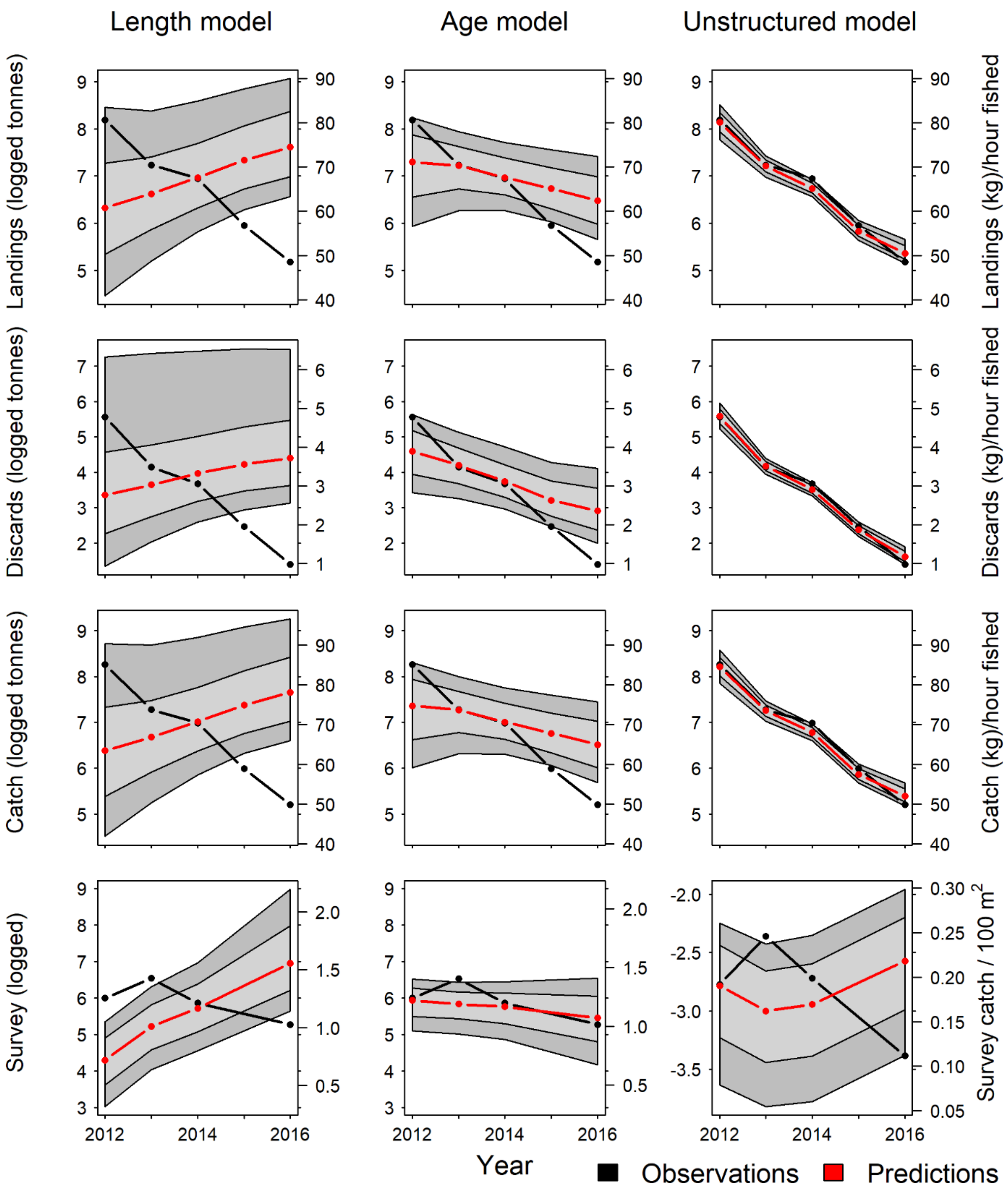


Figure 4.11: Stock assessment model fits to four sets of data. Column 1 is the length-structured model, Column 2 is the age-structured model and Column 3 is the unstructured model. Values are reported on a natural logarithm scale for presentation purposes. Row 1 is natural logarithm annual tonnes landed, Row 2 is natural logarithm annual tonnes discarded, Row 3 is natural logarithm annual tonnes caught (landings + discards) and Row 4 is natural logarithm survey data. The survey data for the length- and age-structured models is natural logarithm total numbers of king scallop caught during the survey, and for the unstructured model this is the natural logarithm total tonnes of king scallop caught during the survey. Year is the x-axis on each plot. Each plot displays a red line which represents the median model estimate for the given metric. The light grey and dark grey areas surrounding the line represents the 75% and 95% prediction intervals in model sampling, respectively. The black line represents the observed trend for each metric. The secondary y-axis (right-hand side) represents a standardisation of each metric and corresponds to the same lines as the left-hand axis. The right hand axes are the metrics in the left hand axes (although not logged) standardised by annual effort (hours fished) in Rows 1 – 3, and standardised by the cumulative area swept by the dredges during the survey each year in Row 4.

Model estimated management metrics

The median estimates of MSY, B_{MSY} and carrying capacity were lowest in the age-structured model (Table 4.8). The un-structured model median estimates of these were very similar to the respective age-structured estimates, although always slightly higher (Table 4.8). The un-structured model had much wider PIs than the age-structured model. The length-structured model median estimates were considerably higher than the other two models, although CIS were a similar width to the age-structured model (Table 4.8).

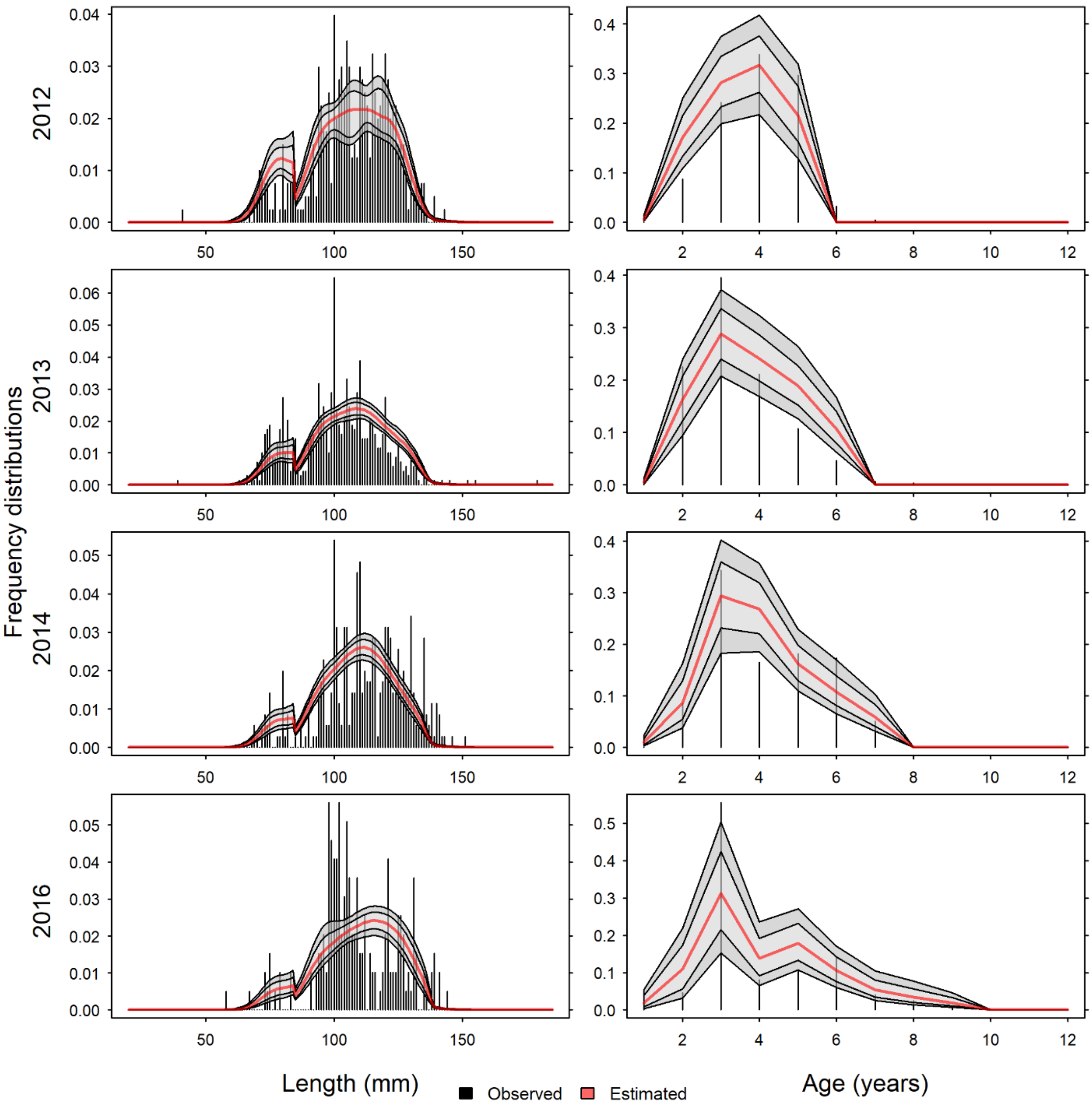


Figure 4.12: Estimated survey frequency distributions compared to observed survey frequency distribution data. The first column is the length-structured fits from the length-structured model and the second column is the age-structured fits from the age-structured model. Each row corresponds to a year of survey data. The bars represent the observed frequencies, the red lines are the median distributions from the respective model, and the two areas around the red lines represent the 75% and 95% prediction interval ranges of the respective model estimates.

Median estimated TSB was higher than the median estimated B_{MSY} in the years 2012 and 2013, and lower in the years 2014, 2015 and 2016 for the age-structured model (Figure 4.18). Overall there was a decreasing trend in median estimated TSB relative to median estimated B_{MSY} with time for this model. Median estimated TSB was always higher than median estimated B_{MSY} in the unstructured model, although the relative stock biomass decreased with time (Figure 4.18). Median estimated TSB was lower than the median estimated B_{MSY} in the years 2012 and 2013, and higher in the years 2014, 2015 and 2016 for the length-structured model (Figure 4.18). Overall there was a rapidly increasing trend in median estimated TSB relative to median estimated B_{MSY} with time for this model. Median relative stock biomass estimates were higher in the unstructured model than the age-structured model across all years. Median relative stock biomass estimates from the length-structured model covered a wider range and were considerably different from the other two models at various points in time (Figure 4.18).

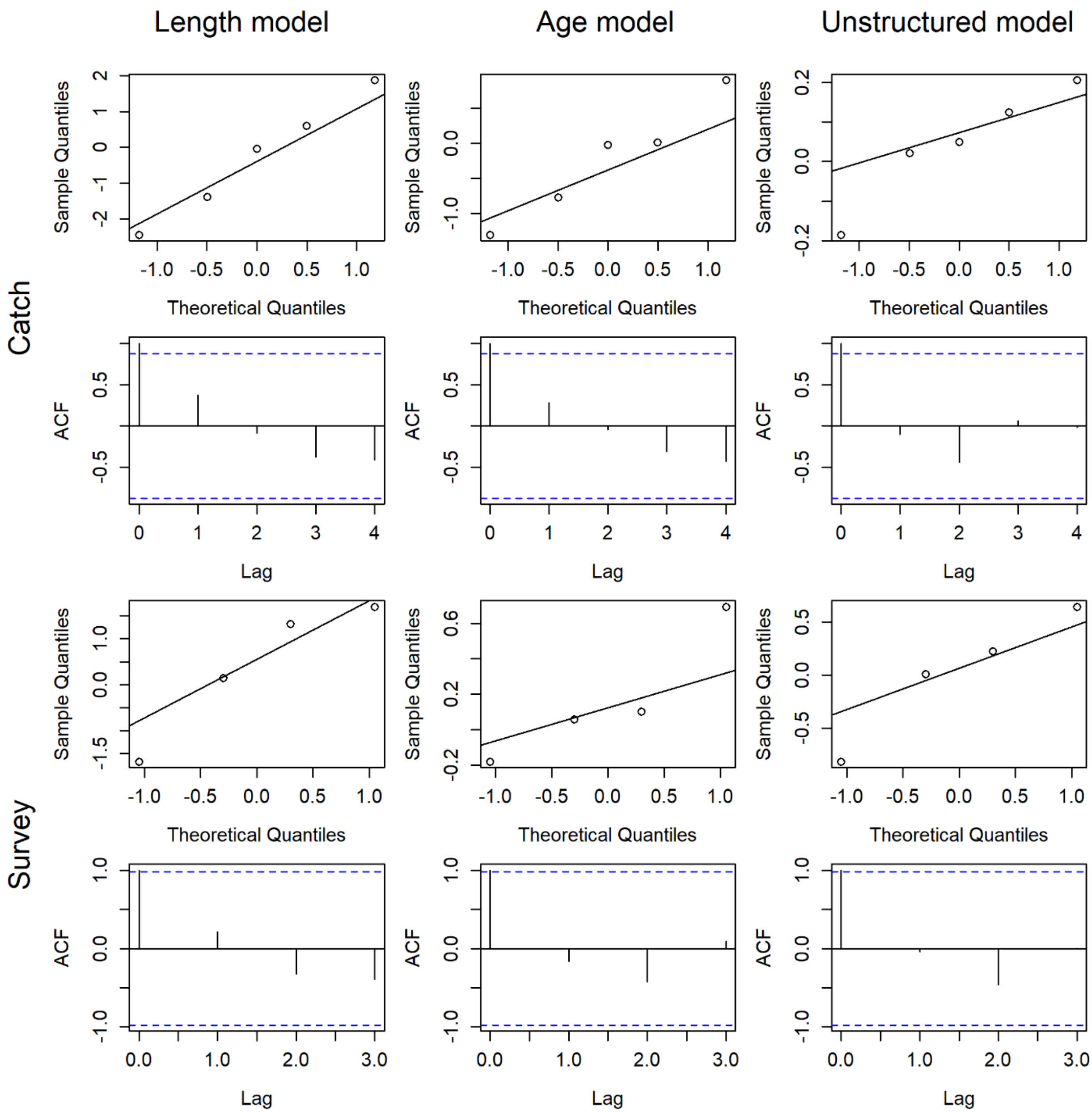


Figure 4.13: Diagnostic plots of the aggregated catches and survey indices from each model. The first column is residuals from the length-structured model, the second column are those from the age-structured model and the third column are from the unstructured model. Rows 1 and 2 correspond to the aggregated catch and rows 3 and 4 correspond to the aggregated survey. Rows 1 and 3 are normal quantile-quantile plots, where the points are expressed on a relative scale and the diagonal line indicates no difference between the two sets of residuals. Rows 2 and 4 are auto-correlation plots to inspect temporal correlation between residuals, where 1 or -1 indicates positive or negative correlation respectively. The unbroken lines indicate the correlation at the each time step (lag one) and the broken lines are included to indicate the correlation thresholds.

Median estimated fishing mortality rate was always considerably higher than the median estimated F_{MSY} for the age-structured model, although the relative trend decreased with time (Figure 4.18). Median estimated fishing mortality rate was higher than the median estimated F_{MSY} in the years 2012, 2013 and 2014, and lower in the years 2015 and 2016 for the unstructured model (Figure 4.18). Overall there was a decreasing trend in median estimated fishing mortality rate relative to median estimated F_{MSY} with time for this model. Median estimated fishing mortality rate was always lower than the median estimated F_{MSY} for the length-structured model, and this trend was relatively constant with time (Figure 4.18). Median relative fishing mortality rate estimates were considerably higher from the age-structured model than the other two models, with the unstructured model median estimates also much higher than the relatively low median estimates from the length-structured model.

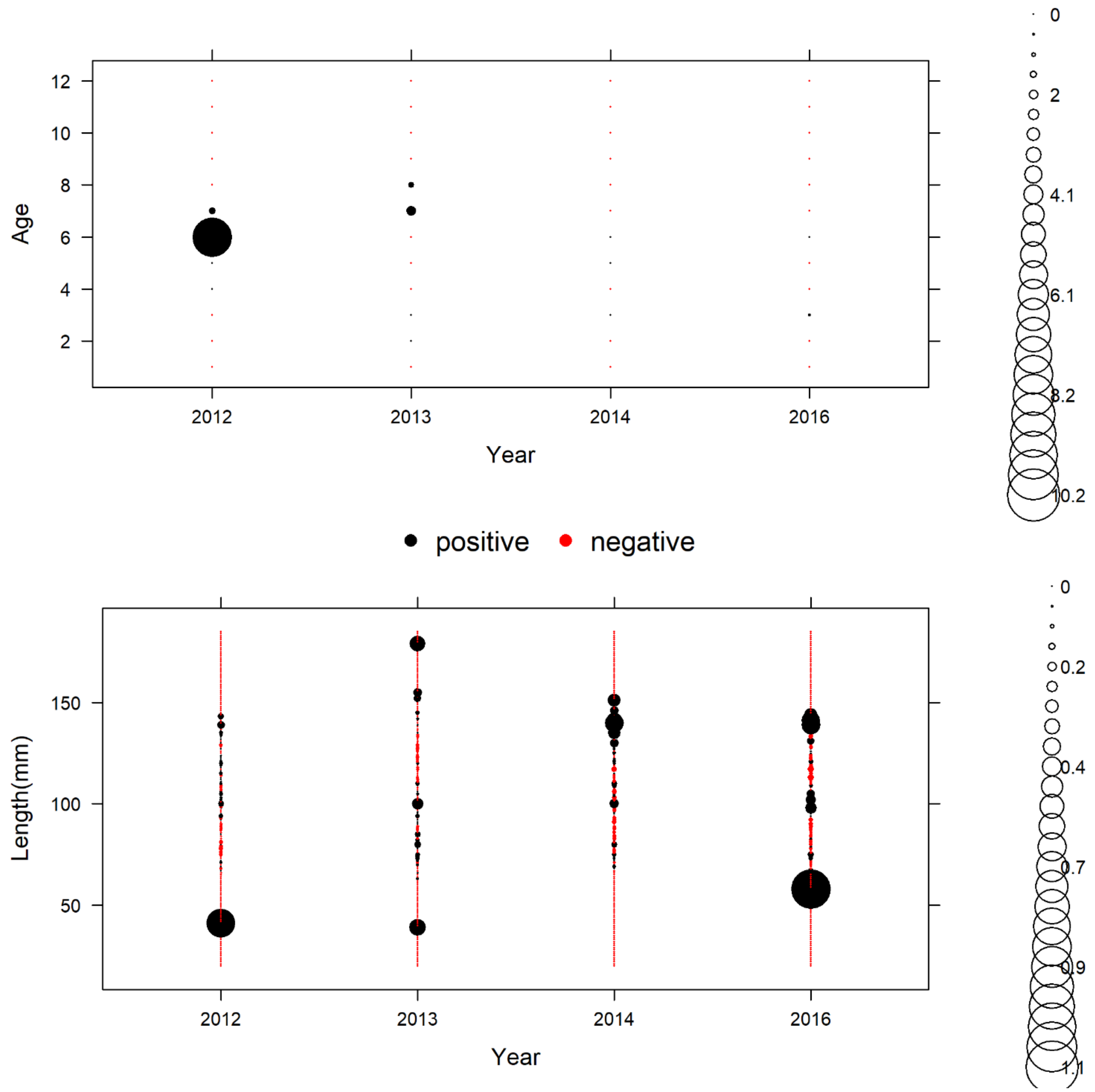


Figure 4.14: Standardised residuals for survey frequency distributions from each of the age- and length-structured models. Residuals are standardised by the standard deviation of observations at that length- or age-class. The x-axis corresponds to annual surveys, and the y-axis corresponds to either length- or age- class. Black circles indicate observation higher than estimate (positive) and red circles indicate observation lower than estimate (negative). Circle size is scaled by magnitude of standardised residual, as indicated by scale bar to the right of each panel.

4.4 Discussion

Model statistical performance and comparison

The goodness-of-fit of each of the models' sets of estimated data to the observed data varied considerably. The length-structured model was the poorest fit to the annual aggregated landings, discards and catch. The age- and un-structured models were much better fits than the length-structure model. The majority of the observed landings, discards and catch all fell within the 95% PI of model estimates for the age-structured model, however the unstructured model had far narrower PIs. The estimated survey index fitted well to the observed data for the age-structured model, but poorly in both the length- and un-structured models. These two models estimated different trends with time to the observed survey indices. These poor fits are likely to be improved by extending the annual surveys to conduct more hauls and sample more of the assessment area, which is crucial for obtaining a representative sample of the stock (Hilborn and Walters 1992). The age-structured model survey frequency distributions were a better fit to observations than the length-structured equivalents. The length-structured model had the greatest number of classes, estimated the most parameters, two more than the age-structured model, and had the additional complexity of explicitly modelling growth using two additional fixed parameters. These factors are likely to have contributed to the poor goodness-of-fit of this model. In addition, it is likely that the length-structured model goodness-of-fit would benefit from further down-weighting of the influence of the length-frequency distribution likelihood on the joint likelihood to allow better fitting to the commercial data. This is considered best practice when IA models struggle to fit to all sources of data in the joint likelihood (Francis 2011; Francis 2017).

The distributions of the observed and estimated aggregated catch residuals were similar for the length-structured model, whereas the age- and un-structured models were more dissimilar. This indicated that the length-structured model's estimated aggregated catches followed the same distribution as the observed annual catches. None of the distributions of observed and estimated aggregated survey residuals were similar for any of the models, indicating different distributions. The model results presented here should be considered with some caution as a consequence of these dissimilarities in distributions. However, all cases of dissimilarity are expected to improve by extending the time series and therefore generating more residuals. The standardised frequency distribution residuals from the age- and length-structured models did not display any strong patterns for trends in extreme residuals, which indicates the model estimated distributions which follow the same distributions as the observations.

Comparison of model estimates

The selectivity curves are difficult to compare directly between the length- and age-structured models due to the differing number of classes and the variation in size of scallops between the age classes. In addition, it is key to note the two MLS in force throughout the assessment area, which undoubtedly added uncertainty to selectivity curve fitting. The length-structured model has likely overestimated l_{50}^{F} (median 107mm), as we would expect full selectivity to occur at 110mm (upper MLS) and l_{50}^{F} to be considerably lower than this. The age-structured model has probably also overestimated a_{50}^{F}(median 3.5 years), as we would expect this to be lower based on size-at-age data, and the resultant curve indicates median full selectivity occurs at age 5, which we would also expect to be lower. Additionally, both a_{50}^{F} and the scale parameter (β^{F}) in the age-structured model were highly dependent on their prior distributions, and therefore the resultant fishery selectivity curve was largely driven by user bias. Similarly, the scale parameter of the retention fraction curves in both models (β^{D}) were highly dependent on their prior distributions, and therefore the resultant retention fraction curves were largely driven by user bias. However, the retention fraction rapidly increased between 95mm and 105mm and ages 2 and 3 respectively and therefore the resultant curves are reasonable, but with some room for improvement in the length-structured model, for a fishery with two MLS (100mm and 110mm). The estimated survey catch efficiency curves had wide PIs for larger and older scallops which implied uncertainty in the parameter estimates for these curves. Once again, the shape (a_{10}^{V}) and scale (β^{V}) parameters for the age-structured survey catch efficiency curve were highly dependent on their prior distributions, meaning the resultant curve was driven by user bias.

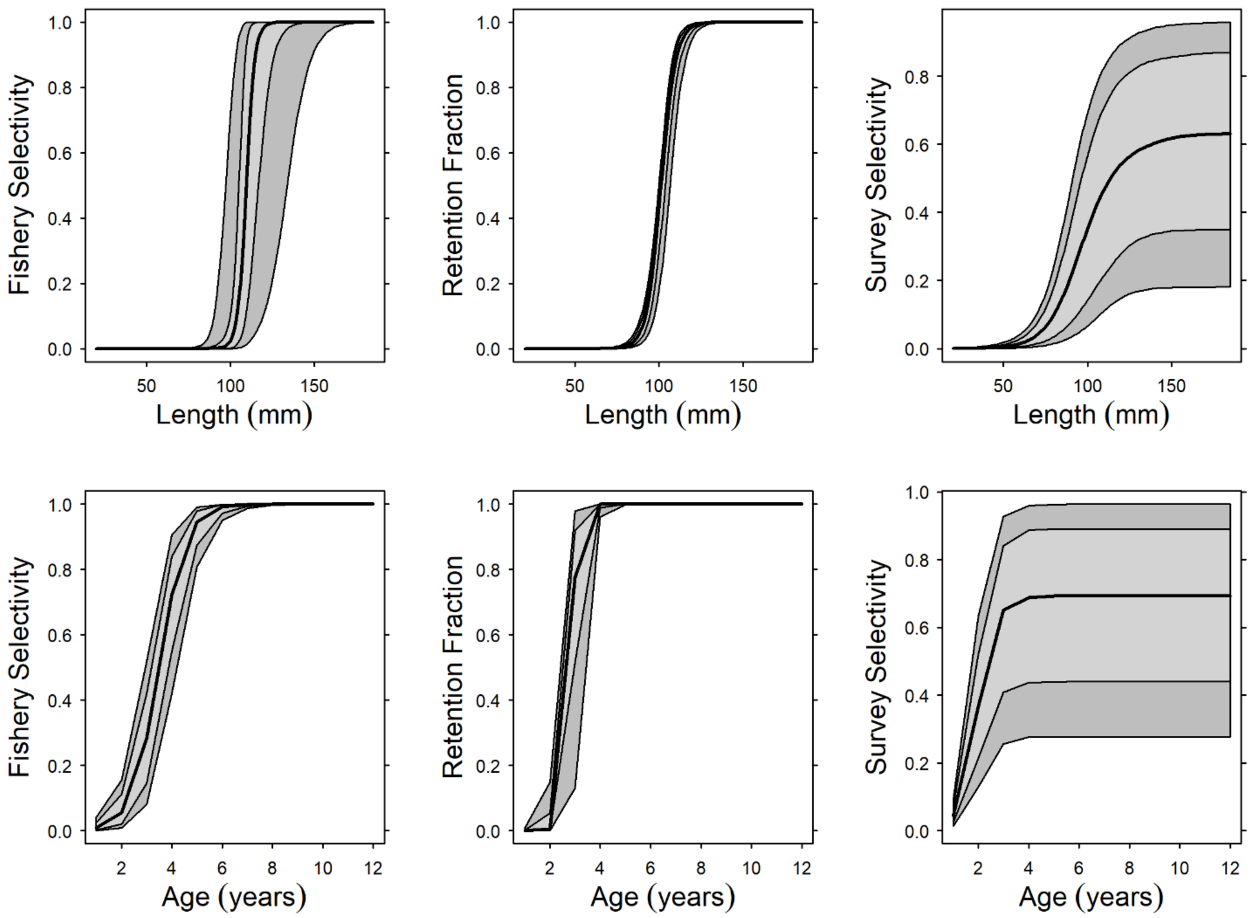


Figure 4.15: Model selectivity curves based on sampled values of shape and scale parameters for each curve. The top row are the curves from the length-structured model, and the bottom row are from the age-structured. The first column is the commercial fleet selectivity, the second column is the commercial retention fraction curve (inverse of discarding) and the last column is the survey gear absolute catch efficiency. On each panel selectivity or catch efficiency is presented on the y-axis and class on the x-axis. The thickest black line is based on median sampled values of the two parameters and the light grey area represents 75% prediction intervals and the darker grey area 95% prediction intervals.

The estimated median survey catch efficiencies (q^{V}) were similar at 0.69, 0.63 and 0.60 for the age-, length- and un-structured models respectively, with the smallest 95% PI range in the un-structured model (0.25 to 0.93) and the largest 95% PI range in the length-structured model (0.18 to 0.96). These estimates from the age- and length- structured models were for the age(s) or size(s) of scallop which the gear caught best, whereas the unstructured model estimates were for biomass of scallops and does not consider size or age structure differences in catch efficiency. Therefore, it is expected that the age- and length-structured estimates should be higher. These median estimates were considerably higher than previous estimates for these dredges (0.29), which was obtained using underwater video footage to count the number of king scallops on the seabed before dredging over (Lambert et al 2014). This method did not account for scallop size or age and therefore is directly comparable to the unstructured model catch efficiency estimate, but the age- and length- structured model estimates should be higher. The median estimates here were also considerably greater than other catch efficiency estimates of Newhaven dredges catching king scallops (0.13 – 0.62) (Chapter 2; Chapman et al 1977; Beukers-Stewart et al 2001), although these Newhaven dredges have a larger mesh size and belly ring diameter and therefore would be expected to have a lower catch efficiency. Similarly, the estimated medians here are much higher than catch efficiency estimates for any other dredge type catching king scallops (0.05 – 0.35) (Baird 1955; 1959; Dupouy 1982). However, catch efficiency estimates as high as the median estimates reported here have been made for other towed gears targeting other species of scallops including Japanese dredges targeting Yesso scallop (*Patinopecten yessoensis*) (0.4 – 0.6) (Kosaka 2016), otter trawls targeting saucer scallop (0.19 – 0.69) (Joll and Penn 1990; Kangas et al 2011) and scientific, modified New Bedford dredges targeting sea scallop on fine substrates (0.64 – 0.71) (Miller et al 2019).

None of the trends in estimated annual fishing mortality rate from each of the models decreased at a similar rate to the decrease in observed effort, which indicated all models may not be capturing the true trend in fishing mortality rate. If fishing mortality rate is directly proportional to observed effort, which remains an assumption, then it is likely to have been challenging for the models to estimate the trend in fishing mortality rate due to the rapid decrease of observed effort with time. Differences existed between the models in estimated fishing mortality rate, with the age-structured estimates consistently highest, and the length-structured model estimates indicated a very shallow decrease in fishing mortality rate with time.

Different trends and magnitudes in stock size estimates (total abundance, TSB and SSB) were estimated between the three models as well. The length-structured model estimated stock size to be rapidly increasing with time whilst the other models estimated decreases in stock size with time, of different magnitudes and gradients. It is key to note these stock size estimates do not include the nearby Cardigan Bay SAC (closed area). The magnitude of median stock size estimates (TSB, as this was estimated for all three models) was assessed by scaling by the estimated survey catch efficiency and then expressed as densities. Each model was deemed to over- and under- estimate TSB throughout the time series, by comparison of these scaled densities to observed survey indices. However, the magnitude of each median stock size estimate was biologically plausible. Median recruitment was 37.1 – 93.6 % of the median total abundance across the time series for the length-structured model and 11.0 – 23.3 % for the age-structured model. The median percentage of recruits estimated in the age-structured model overlapped with the range of estimated percentage of recruits in the USA East Coast sea scallop (*Placopecten magellanicus*) fishery (17 – 35 % of the total abundance) (Aldous et al 2013), which may indicate that the magnitude of estimated recruitment was sensible in the age-structured model.

The length-structured model had considerably greater estimates of median MSY, B_{MSY} and carrying capacity compared to the other models. The median MSY estimate from the length-structured model was much larger than the observed landings in any year (178.1 to 3605.7 tonnes). This was a consequence of a large, and increasing with time, annual TSB estimate, indicating that a greater yield could be sustainably harvested. The median estimates of MSY, B_{MSY} and carrying capacity were similar between the age- and un-structured models, but the unstructured model was consistently higher. The stock size (TSB) relative to the B_{MSY} was highly varied between the models. The median relative stock size was above one for the entirity of the time series for the unstrucutred model, indicating the stock size much was larger than the B_{MSY}. However, the median relative stock size was only above one for the first two years in the age-strcutured model and only above one for the final three years in the length-structured model. The median relative stock size for the other years from these models was below one, indicating that the stock size was below the B_{MSY} in each of these years. Therefore, there are clear differences in estimated stock size realtive to the biological reference point B_{MSY} with time between the three models.

Similarly, the model outputs also disagreed on the estimated annual fishing mortality rate relative to estimated F_{MSY}. Median relative fishing mortality rate was extremely high and well above one for each year in the time series in the age-structured model, indicating the estimated annual fishing mortality rate was considerably larger than the estimated F_{MSY}. In contrast, the median relative fishing mortality rate from the length-structured model was well below one for each year which indicated the annual fishing mortality rate was lower than the F_{MSY}. The unstructured model output disagreed further, with relative median stock size above one for the initial three years in the time series and below one for the final two years. However, the median relative fishing mortality rate was very similar between the length- and un-structured models for 2016. It should be noted that additional observation error may have not been captured in the estimates of MSY, B_{MSY}, F_{MSY} and carrying capacity in the length- and age-structured models as these used a secondary model to estimates these values, unlike the unstrucutred model which estimated these values *in situ*. Therefore these estimates should be treated with additional caution in the age- and length-structured models.

The differences in stock size trend with time between the length- and age-structured models is likely to have been caused by the different frequency distributions when the stock was structured by length or by age and the effect of each model's fishery selectivity curve. The shape of the age-structured survey distribution differed from the length-structured survey distribution (Figure 4.12), in that a higher proportion of the stock were contained in classes to the left of the distribution. This was because key age classes (such as age two and three) span a broad range of king scallop sizes due to higher growth rate variability at young age classes. The age-structured fishery selectivity curve increased quickly with increasing age (as scallops of age two and three can be large enough to be caught and landed), compared to the length-structured fishery selectivity curve which maintained low selectivity and increased later in the frequency distribution. From model testing, this combination of left-skewed population structure and fishery selectivity curve resulted in the decreasing trend in stock size with time in the age-structured model. The differences in stock size trend caused by these effects is likely to be reduced by down-weighting the influence of the frequency distributions on the joint likelihood of each model (Francis 2011; Francis 2017).

Another source of variation between the models may have been caused by parameter confounding, which is known to be a greater issue in length-structured models than age-structured models (Punt et al 2013). Parameter confounding is when a parameter value affects another parameter value, and as a result the model may struggle to estimate the two parameters independently. In particular, the natural mortality rate can become confounded with fishing selectivity (Punt et al 2013) and this may have been more serious in the length-structured model. It is also evident that the age- and length-structured models are sensitive to the chosen natural mortality rate, however as there were little trends evident from the sensitivity analysis it is not true that alternative values of natural mortality rate would reduce differences in model estimates. The difference between the trends in estimates may also be a consequence of the short time series, poorly described growth, or differences in recruitment definition and estimation (Punt et al 2013).

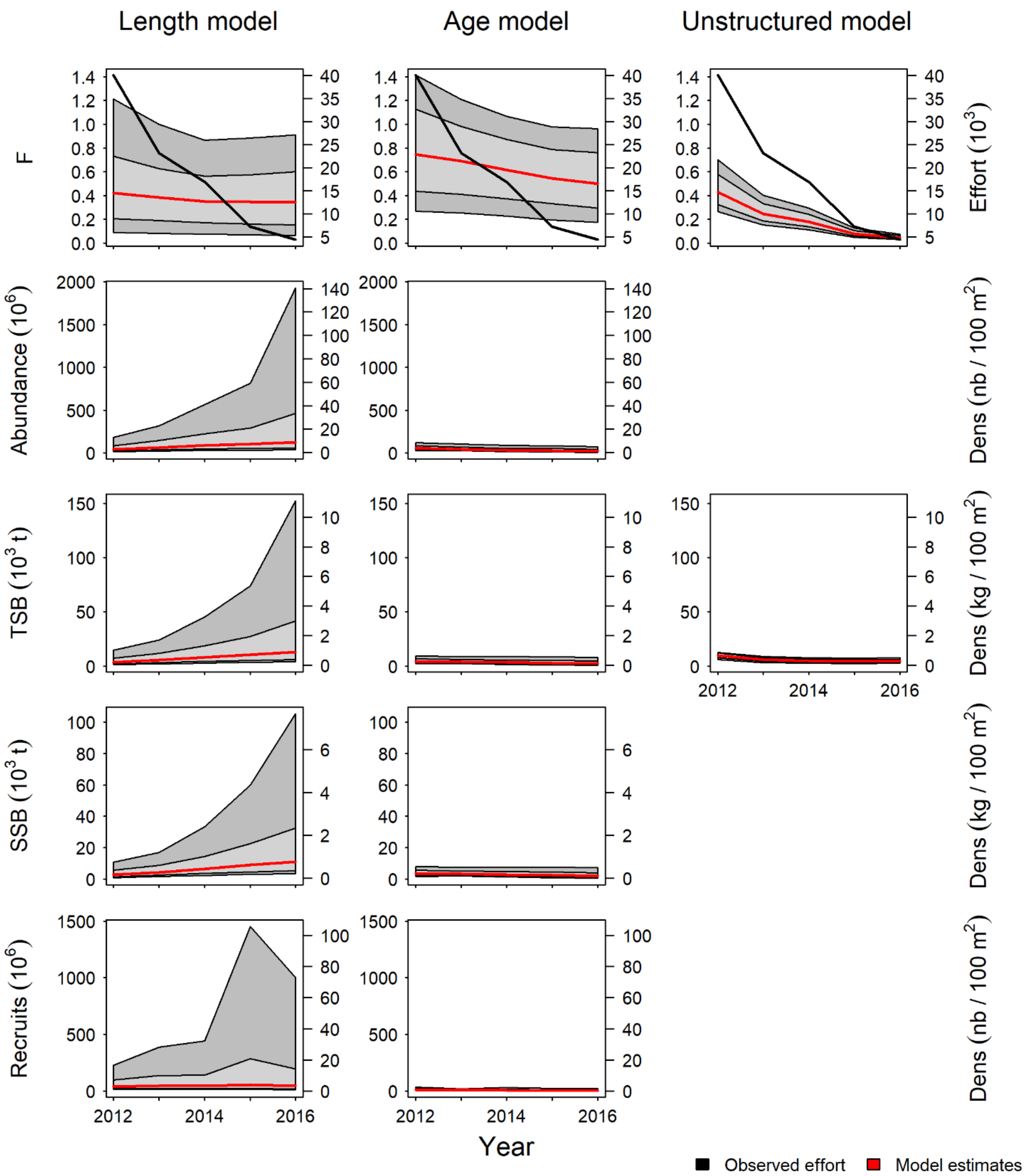


Figure 4.16: The main outputs from each of the three stock assessment models. Column 1 is the length-structured model, Column 2 is the age-structured model and Column 3 is the unstructured model. Row 1 is fishing mortality rate (averaged across scallops > 110 mm shell width), Row 2 is total stock abundance (expressed as millions of scallops), Row 3 is TSB (thousands of tonnes), Row 4 is SSB (thousands of tonnes) and Row 5 is total number of recruits (expressed as millions of recruits). Only two panels are presented for the unstructured models as the missing metrics were not explicitly estimated by this model. On each panel year is on the x-axis. Each plot displays a red line which represents the median model estimate for the given metric. The light grey and dark grey areas surrounding the line represents the 75% and 95% prediction intervals in model sampling, respectively. The black line on the fishing mortality panels represent observed effort (thousand hours fished) throughout the assessment area, and corresponds to the secondary y-axis (right-hand side). For the other panels the secondary y-axis represents each metric divided by the total size of the assessment area, to express the metrics as densities, and therefore these axes also correspond to the red lines and shaded areas indicating prediction intervals.

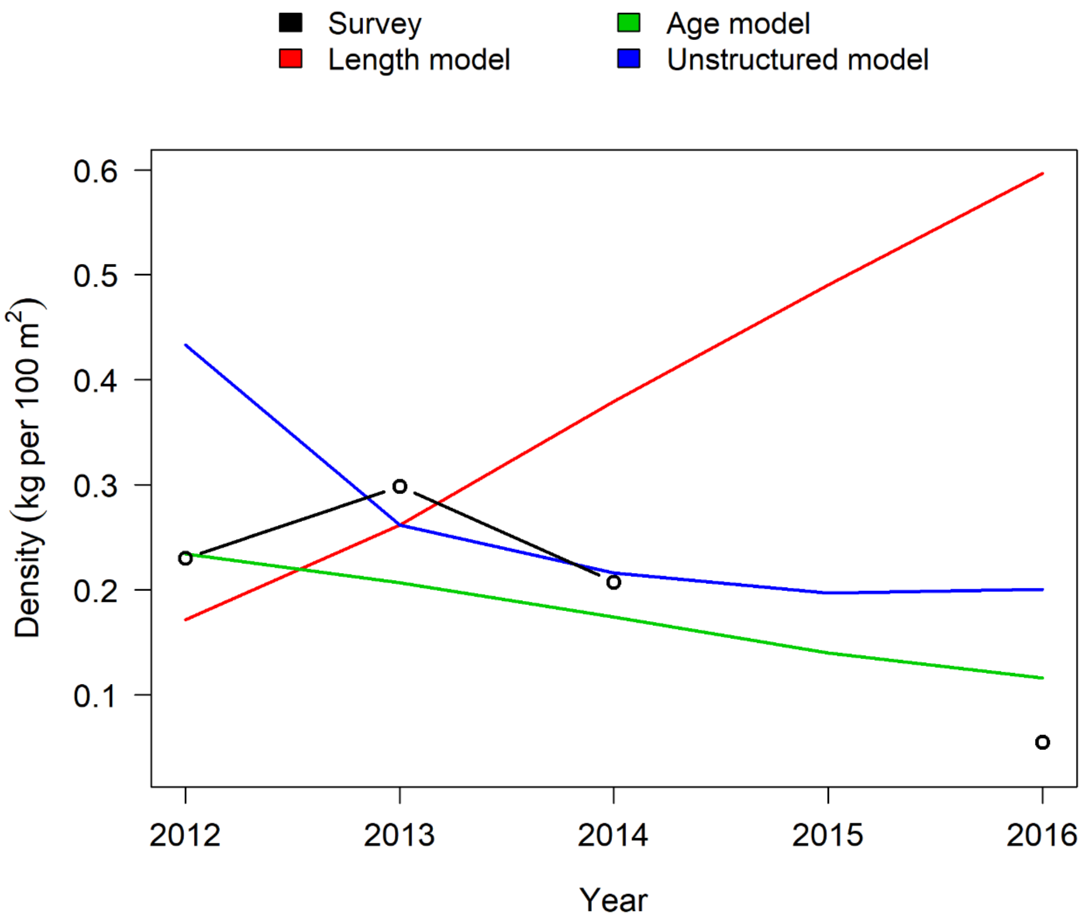


Figure 4.17: Comparison of observed survey indices with stock assessment model median TSB estimates. The black line and points represent density of total survey catch (kg caught per 100 m^2 of seabed fished). The red, green and blue lines represent TSB multiplied by the respective median estimated survey catch efficiency (q^V) and expressed as density (kg per 100 m^2 of the assessment area) from each of the length-, age- and un-structured models respectively.

Table 4.8: Median and PI estimates of maximum sustainable yield (MSY), the stock biomass at MSY (B_{MSY}) and the stock carrying capacity for each of the age- length- and un-structured models. Note these estimates from the age- and length-structured models are derived from a secondary unstructured model fit to the age- and length-structured model stock biomass estimates to estimate the parameters r and K, used to calculate these displayed estimates. The primary unstructured model displayed in the table computes these estimates directly within the model.

Metric	Estimate	Age	Length	Un
MSY (Tonnes, live weight)	95% PI	1002.9	7147.3	1505.6
	Median	364.3	4757.7	498.1
	5% PI	49.1	2098.9	125.7
B_{MSY} (Tonnes, live weight)	95% PI	5403.7	9668.4	8344.0
	Median	3881.3	6749.0	4139.2
	5% PI	2256.7	5167.5	2630.0
Carrying capacity (Tonnes,	95% PI	10807.3	19336.8	16688.0
live weight)	Median	7762.5	13498.0	8278.5
	5% PI	4513.4	10335.1	5260.3

On balance there are arguments for either the age- or un-structured models performing best with these datasets. The unstructured model had the best goodness-of-fit to the observed commercial data, and the age-structured model had the best goodness-of-fit to the observed aggregated survey indices and reasonable goodness-of-fits to the observed commercial data and observed survey age-frequency distributions. Both of these models produced similar estimates of median MSY, B_{MSY} and carrying capacity, which were a more realistic magnitude relative to the observed landings than the length-structured model estimates. The length-structured model also had the worst statistical goodness-of-fit.

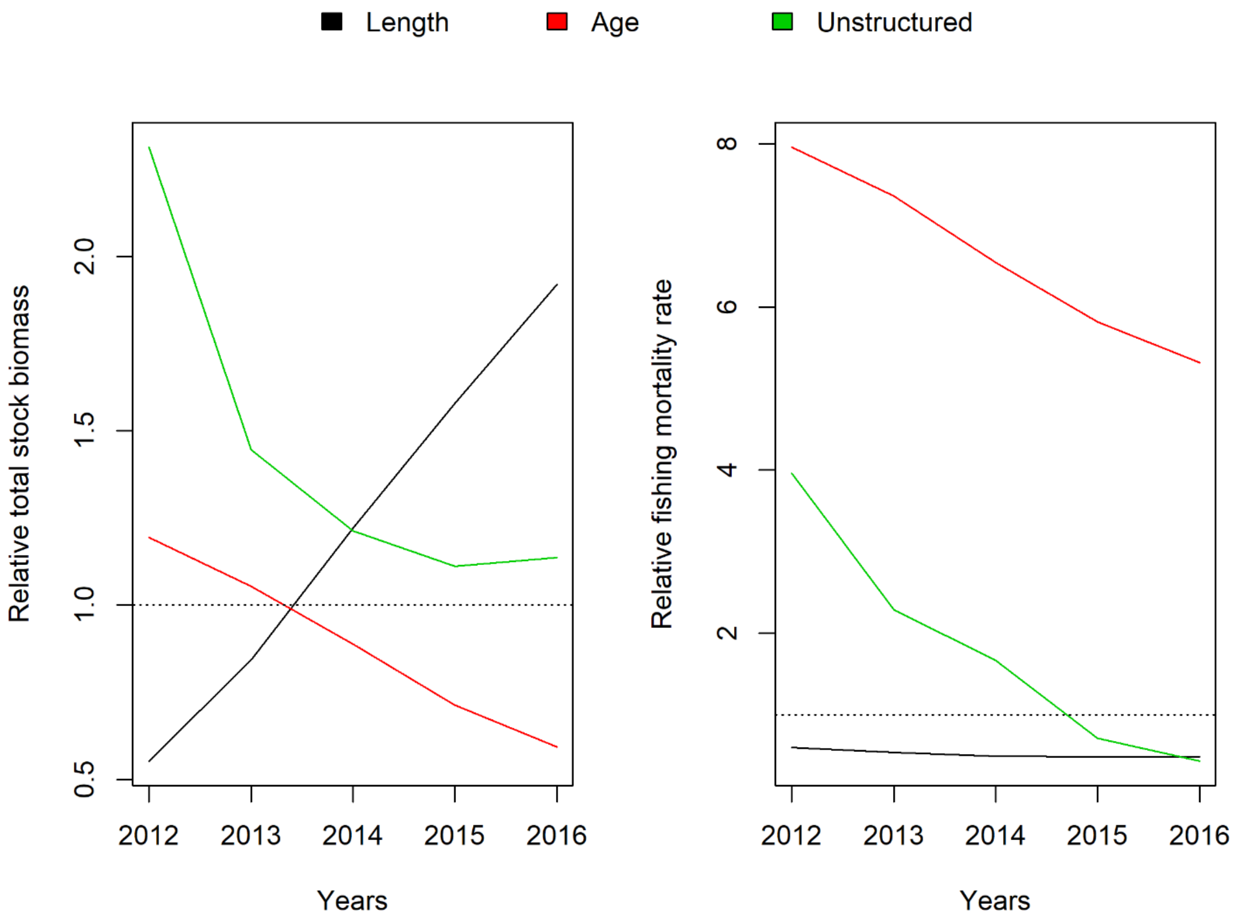


Figure 4.18: The changes in relative total stock biomass (left) and relative fishing mortality rate (right). Relative total stock biomass is the median estimated annual TSB divided by the median estimated B_{MSY}, and relative fishing mortality rate is the median estimated annual fishing mortality rate divided by the median estimated F_{MSY}. In each panel the x-axis displays years and the dashed line indicates the point where median estimated TSB or fishing mortality rate equals B_{MSY} or F_{MSY} respectively. The other lines are coloured by model type, as indicated in the plot legend.

This work reinforces that the costs and benefits of using age- or un-structured models for stock assessment is complex and case dependent. Both our age- and un-structured models produced reasonable and sensible estimates of stock size, which contradicts studies which have found unstructured models incapable of doing this (Townsend 1986; Bjorndal and Brasao 2006; Tahvonen 2008). Likewise, our work here also disagrees with other studies which have reported poor fits between observations and estimates from unstructured models (Massey et al 2006; Jonsen et al 2009). Our study is in agreement with other studies which have shown unstructured models can estimate key metrics as well as age-structured models (Ludwig and Walters 1985; 1989; Moxnes 2005). In those studies the key metrics were optimal effort and economic revenue, and therefore different to the key metrics analysed here. The age-structured model implemented here had greater data requirements and was more complex than the unstructured model, but as a consequence provided greater detail and was capable of estimating additional pieces of information such as recruitment and SSB. The age-structured model is also be capable of estimating age-structured fishery selectivity and retention curves and an age-structured survey absolute catch efficiency curve when more informative data are available, as has been shown with recent applications of the age-structured model to the Isle of Man king scallop fishery (not displayed here). The trade-off between data requirements, complexity and detail of outputs is a subject for consideration for future assessment analysts.

Stock status and management advice

The age- and un-structured models both showed that the stock size decreased with time, although there was a marginal increase in median estimated stock size between 2015 and 2016 in the unstructured model. The observed annual survey indices also decreased with time, after 2013, and therefore it is highly likely the stock size did decrease with time based on these three pieces of evidence. The median estimated stock size (TSB) was 2,229 tonnes and 4,571 tonnes in 2016 from the age- and un-structured models, respectively, meaning there was still clear discrepancy between the stock size estimates. The median estimated MSY was 364 tonnes and 498 tonnes from the age- and un-structured models, respectively, again indicating some differences in model estimates. Due to model estimate uncertainty, it is recommended that a total allowable catch (TAC) between the lower 95% prediction intervals of each of the age- and un-structured model estimated MSY (49 to 126 tonnes) is set for the assessment area. Advice from the length-structured model is not considered here due having the worst fits of estimated data to observed data.

Enforcing catch limits upon the Cardigan Bay stock would also have considerable management challenges. There is currently no licencing for the assessment area and therefore no way to control the number of vessels or how much they each land. Implementing a licencing system would also be challenging as an agreement would need to be formed between both the EU and Wales so that the licencing would apply to both Welsh waters and EU waters (as both are in the assessment area). In addition, it is also likely to be challenging to determine whether landings from the Cardigan Bay stock were obtained from the assessment area or outside under the current reporting system and as a result catches may be biased. However, the conversion of catch limits to an effort-based approach, such as a daily or weekly limit on fishing time, may be more appropriate for this fishery in an attempt to limit fishing effort further. However, applying further effort restrictions in only Welsh waters is likely to result in a displacement of effort to the part of the assessment area in EU waters.

Another key management consideration for these models is the spatial area where the models were applied. Total landings (from all nations, not just UK) used here were reported by ICES statistical rectangles, such as the assessment area. Accurate total removals from the stock through fishing is important, as fishing pressure is likely to be biggest driver of stock size. However, these rectangles are not aligned with local spatial management in Wales. As a consequence of well-intentioned local management, the assessment area has two MLS enforced (one inside and one outside 12nm line), and there is currently no requirement for vessels to declare which management zone they were fishing in. A solution should either result in landings being reported in accordance with local management regimes or the MLS standardised between the two management zones.

Methodological considerations and future development

The fitting of each model was time consuming, as suitable prior distributions had to be identified for all estimated parameters and each model had initial convergence issues due to the short time series. The Stan software and HMC method are thorough methods for exploring the joint posterior distribution of each model and highlighted when the algorithm had difficulties finding numerical solutions when inappropriate prior distributions had been specified for parameters. Some estimated parameters had fairly intuitive prior distributions which were based on knowledge of what values the parameters should take, however other estimated parameters (such as the historical recruitment) were less intuitive and the prior distribution was set through trial and error, within sensible ranges, until the model was able to converge to a numerical solution. Wide priors were set for such parameters to reduce user bias in the prior distributions, but these prior distributions were bounded at sensible limits, which introduces some user bias, to prevent sampling of unrealistic parameter values and reduce computational time. Hyperpriors, where the median and standard deviation of a prior were each determined with further priors, were implemented for the annual recruitment parameters to further reduce user bias on these parameter estimates.

Strong user bias was existent in the posterior distributions of multiple estimated parameters in the length- and age-structured models, likely due to the high number of estimated parameters relative to the available data which may have been relatively uninformative due to the short nature of the time series (Hilborn and Walters 1992; McAllister and Ianelli 1997). Reducing the number of estimated parameters in each model, by estimating these parameters as fixed parameters, can reduce parameter uncertainty and variance on model outputs (such as stock size or fishing mortality rate) (Hilborn and Walters 1992). However, the fixed value of a parameter would need to be determined from a field study, separate data analysis or literature review. In particular, research to determine the parameters of any of the three selectivity curves estimated in each of the length- and age-structured models would likely result in improved overall model performance. Experiments to define the selectivity of both landings and discards in commercial dredges and the survey dredges could be conducted by comparison of catch rates from multiple gear types (e.g. Hamley and Regier 1973; Millar 1992). Alternatively, tag and recapture studies could also be employed to achieve this (e.g. Anganuzzi et al 1994; Myers and Hoenig 1996). Absolute catch efficiency, estimated in all three models, could be estimated by a depletion study (Beukers-Stewart et al 2001; Rago et al 2006), with divers (Beukers-Stewart et al 2001; Fifas et al 2004), using optical methods (Lambert et al 2014; Miller et al 2019), by mark-recapture (Dickie 1955) or by dredging over known abundance on seeded grounds (McLoughlin et al 1991).

Conversely, the fixed von Bertalanffy growth parameters may be estimated within the model in the future when a longer time series is available. Although this would require two more parameters to be estimated, the advantage is that the growth parameters would be more consistent with the model's estimated stock (Punt et al 2013). The king scallops used to estimate the growth parameters were obtained with dredge fishing gear, and therefore gear selectivity will have restricted the description of small king scallop growth rates in the von Bertalanffy curve (Hilborn and Walters 1992), and therefore internal estimation of growth parameters may improve the length-structured model. Time-varying growth parameters may also be more appropriate for a longer time series where growth rates may change with time (e.g. Szalai et al 2003). Growth could also be modelled using a multinomial process, which would explicitly capture the true nature of growth rather than using approximations from a von Bertalanffy curve (Punt et al 2010).

Length-structured and age-structured models have been shown to produce inconsistent estimates of biomass when data are limited (Jonsen et al 2009) and the performance of all three models is likely to improve considerably with an extended time series, both in terms of individual model goodness-of-fit and a reduction in the differences in estimates between the three models (Hilborn and Walters 1992). The time series was short relative to the lifespan of the target species (> 10 years) and the commercial catches had a relatively high coefficient of variation (1.05). Increasing the time series is more likely to capture extreme situations which would help define the upper and lower limits of parameter values (Hilborn and Walters 1992). The length of the time series for the US east coast sea scallop length-structured stock assessment model (> 40 years) is considered a major reason for its ability to produce good estimates of stock size

(Anhalzer et al 2018). Initial testing of the models applied here with a longer king scallop data time series from the Isle of Man has indicated improved model performance (not presented here). Although catch data were available prior to 2012 for the Cardigan Bay fishery, neither of the length- or age-structured models would have been able to determine stock structure without survey frequency data, and survey indices also help tune the magnitude of estimated stock size in all three models. Therefore, it was not possible to extend this data time series earlier than 2012. However, it is essential that landings, discards and survey data are collected in the future to build the Cardigan Bay king scallop data time series.

This study used landings data from the 2017 Data Collection Framework data call at the European Union to assess fisheries effort regimes (STECF 2018), which meant that all landings and effort data by member states were collated by ICES statistical rectangle. The restriction of this analysis to a single rectangle may have resulted in a failure to capture the dynamics of the parts of the larger stock in the neighbouring ICES statistical rectangles and closed area (Hilborn and Walters 1992). In particular, the biomass of king scallops in the neighbouring closed area within ICES statistical rectangle 33E5 is almost certainly important, and is likely to be contributing larvae to the assessment area and therefore research of the link between the closed area population size and the assessment area stock size is strongly encouraged through the continuation of fishery-independent surveys (Punt and Methot 2004; Pinchin and Wilberg 2012). Spatially explicit age- and un-structured models considering both open and closed areas have been shown to better estimate stock size and fishing mortality rate than equivalent models applied separately to the open and closed areas (Punt and Methot 2004; Field et al 2006; Pinchin and Wilberg 2012), and therefore the models should be developed to spatially explicit versions to encompass this neighbouring closed area. A large closed area, such as the closed area in 33E5, is likely to result in greater accuracy of model estimates, provided a measure of relative abundance is available for the closed area (Punt and Methot 2004; Pinchin and Wilberg 2012). The scientific survey used in the models implemented here also samples in the closed area, so such a measure of relative abundance is available for the time series implemented here. However, these spatially explicit models require an additional parameter, or an age- or length-structured curve governed by multiple parameters, to describe the migration rate of the stock (both larvae and adults) between open and closed areas (Pinchin and Wilberg 2012). Either prior quantification of these parameters would be required, or they would need be incorporated as new estimated parameters in each model.

In the future, researchers wishing to implement this model for ICES statistical rectangle 33E5 will need to obtain landings data separately from each of the individual nations landing king scallops in the assessment area, as these landings are not routinely collected together. Alternatively, the model may be applied to another area where total landings can be appropriately defined. The discard rate data were obtained from a subset of commercial vessels and the number of vessels sampled should be expanded through a larger observer programme. A larger discard observer programme may also help to further quantify the different discarding rates that occur in line with the two MLS. The survey should also be adjusted to cover the entire assessment area, and with more hauls, as this is extremely important for capturing length-, or age- distributions and survey indices that are representative of the entire stock (Hilborn and Walters 1992).

These models were implemented as IA models to obtain reliable estimates of the uncertainty in model estimates and efficiently utilise multiple observed datasets. Modelling additional observed datasets may be a useful avenue for future model development to account for further uncertainty (e.g. Methot and Wetzel 2013). For example, observed fishing effort data can be modelled to help tune fishing mortality to the correct trend and magnitude in each of the length- and age-structured models (Xiao 1998). Tagging data could be obtained and modelled to help estimate growth, address parameter confounding and can be modelled as a secondary set of survey data to better estimate abundance in the length-structured model (Punt et al 2013; Hillary and Eveson 2015). Environmental data could be modelled if a recruitment relationship was defined, or environmental variables may be directly linked to stock size (e.g. Haltuch and Punt 2011). King scallop recruitment has been shown to be affected by mean spring sea temperature, availability and quality of larval settlement habitat and chemicals used in the netting of salmon farms (Minchin et al 1987; Shephard et al 2009; Howarth et al 2011). In addition, other scallop fisheries have reported a wider range of factors affecting recruitment including predator abundance, presence of invasive species, algal blooms, density of the spawning scallop stock, hydrodynamic conditions, disease and physical disturbance (Summerson and Peterson 1990; Hart 2006; Morris et al 2009).

The fixed natural mortality rate parameter used in the age- and length- structured models was based on a sensitivity analysis to find a value which did not cause model fitting problems and was similar to values used in other king scallop stock assessments (Table 1.5). Natural mortality is notoriously difficult to quantify, as fishing and natural mortality quickly become confounded in an active fishery (Hilborn and Walters 1992; Hewitt and Hoenig 2005). The approach applied here, estimating natural mortality based on the values used in other fisheries' stock assessments, was the best approach with the available data and is commonly practiced (Hewitt and Hoenig 2005). Ultimately, however, there is no available evidence whether this value was appropriate for this Welsh king scallop stock. Furthermore, it is likely that age- or length- structured natural mortality estimates would improve estimates through increased biological reality as natural mortality would be expected to differ with age or length. This is true for the US Georges Bank sea scallop stock assessments, which showed improved fits to survey data using size-dependent natural mortality rates when compared to stock assessment model runs using size-independent natural mortality rates (NEFSC 2014).

Alternative approaches

Alternatively, the fishery stock status may be managed by using trends in survey indices or catch rates as a measure of relative stock size. However, neither of these methods can be used to estimate absolute abundance or estimate B_{MSY} without extensive research of the absolute or relative catch efficiencies of the gear. In addition, commercial catch rates can result in hyperstabilility, where catch rates remain high despite stock abundance decreasing, and is common in fisheries with high searching efficiency (Hilborn and Walters 1992). The reverse, termed hyperdepletion, is also possible in fisheries where a large part of the stock may be inaccessible to fishing (Hilborn and Walters 1992). In either scenario, changes in commercial catch rates do not reflect changes in stock abundance and are therefore often unreliable to assess stock status through time (Williams et al 2010). Other methods exist to estimate stock size from fishery-independent data, such as the conversion of survey indices to abundance (Williams et al 2010). To implement such a method for this fishery, more detailed surveying of the assessment area and a greater understanding of absolute catch efficiency, which would be used to scale indices, would be required.

A key benefit of the stock assessment models implemented here is the additional useful pieces of information estimated alongside stock size, and these are useful for other analyses (such as per recruit analyses or scale survey indices using catch efficiency) or as other model prior distributions in this fishery or other scallop fisheries. The stock assessment models could also be extended to be able to forecast and conduct testing of harvest control rules, which is often not possible with other methods. In addition, these IA models provided the opportunity to efficiently utilise all available data (Maunder and Punt 2013).

The length of the available time series meant this fishery was data-limited, but only relative to the data requirements of the stock assessment models implemented. Several other methods have been developed to estimate single species stock size in cases where data are far more limited than here (Dowling et al 2019). The methods are wide ranging (see Dowling et al 2019), and the demand from management bodies for assessed fish stocks has resulted in generic methods that can be implemented with limited scientific expertise (Dowling et al 2019). These methods typically use calculations for which the assumptions are broad enough to reflect the population dynamics of many fish stocks, and parameters are often taken from other data-rich species (known as the "Robin Hood" approach) (Punt et al 2011; Kokkalis et al 2017). Information from other species can be incorporated directly, as a prior distribution on a parameter, or several single species assessments may be conducted simultaneously to make use of survey indices that apply to species with similar life histories (Punt et al 2011). These methods typically conduct extensive simulations to help build confidence in their outputs (Kokkalis et al 2017) and can be developed as 'tools' designed for quick and simple data-limited stock assessment (Dowling et al 2019). These methods were not considered here as, firstly, although not necessarily collected for the application of the IA models applied here, a broad range of data were available for this stock, and secondly, the application of generic data-limited methods often make, or violate, multiple assumptions and may fail to address inconsistencies in available data (Dowling et al 2019). The approach taken in the present study incorporated careful understanding and analysis of available data, detailed understanding of the underlying calculations and assumptions in the methodology and the models were tailored to the specifics of the fishery.

Conclusions

It is likely that the true stock size decreased with time, based on the estimated outputs of the age- and un-structured models and the trend in observed survey index. Many other useful metrics were estimated by the two best performing models including estimated annual fishing mortality rates, annual recruitment, MSY, biological reference points, fleet catchability, age-structured fishery selectivity, discard retention and survey catch efficiency curves. Multiple fixed parameters were also estimated prior to model fitting including parameters for von Bertalanffy growth, age-weight and length-weight curves. All of these fixed and estimated parameters are directly useful to the fishery in the future, and some will also be directly useful to other king scallop fisheries. Many of the parameters would also be useful as prior distributions in assessments of other fisheries.

The age- and un-structured models produced sensible estimates for the majority of metrics scrutinised. Several of these metrics were similar between the two models, indicating that the differences in stock structure led to only minor differences in some model estimates (MSY, B_{MSY} and carrying capacity). However, relative estimates of stock size and fishing mortality rate were quite different. On balance, we believe either of these models would be a suitable tool for estimating the absolute size of this stock, and many other aforementioned metrics, but are likely to require additional data to be able to estimate relative stock size and relative fishing mortality rate. The ability to obtain similar stock estimates is in agreement with previous studies that have found either age- or un-structured models to be suitable for stock assessment in other fisheries, but in disagreement with the findings of other studies. The age- and un-structured models performed considerably better than the length-structured model which performed poorly. Therefore, the current outputs from the length-structured model should not be considered by management.

The performance of all three models is expected to improve further with an increased data time series, and initial testing of these three models on a longer data set from the Isle of Man king scallop fishery has indicated improved model performance. Therefore, it is recommended that all three models are implemented with a longer time series to further judge the suitability of each model for stock assessment of this king scallop stock. Alternatively, it may be preferable to continue to implement each model to obtain three estimates of key stock management metrics. A single model, or all three models, could be used by management to guide management tools to sustainably manage the stock in the future.

CHAPTER 5: DISCUSSION

This chapter summarises what was learned in Chapters 2, 3, and 4, and how these pieces of work contribute towards the broader aims of the thesis. The aims were to estimate two key pieces of evidence important for the sustainable management of the Cardigan Bay scallop fishery; the absolute size of king scallop populations in the area and the effect of a unit of fishing effort on both the target species and the wider ecosystem. Data limitations which may apply to multiple chapters are also discussed. This chapter then discusses the wider uses and implications of the work to scientists and other fisheries, before discussing the implications of the work for the sustainable management of local Welsh scallop stocks. In particular, strategies are proposed to use, and build on, the findings of the thesis to sustainably manage the Welsh stocks. Lastly, many of future improvements to the work produced here, and the remaining gaps in the data required to sustainably manage the fishery, are addressed. Suggestions are made for future research to address these improvements and data gaps.

5.1 Key findings and estimates

King scallops are of high value to the UK, and in particular Wales (MMO 2018). However, fishing for scallops with dredges is controversial and often negatively impacts the wider ecosystem (Stewart and Howarth 2016). In addition, king scallop landings have decreased in Wales since 2012 (MMO 2018). Because of this high commercial value, scallop dredge impacts on the wider ecosystem and the decrease in landings, it is imperative that Welsh king scallop populations are managed with tools that are based on scientific evidence. This thesis aimed to provide quantitative evidence, based on fisheries monitoring data, which could be used to support the sustainable management of Welsh king scallop populations and the environmental and economic impacts of fishing these. The thesis focussed on methodologies used to estimate two key pieces of evidence important for the sustainable management of the Cardigan Bay scallop fishery; the absolute size of king scallop populations and the effect of a unit of fishing effort on both the target species and the wider ecosystem.

Collectively two of these three chapters (2 and 4) have conducted work towards three of the four general approaches listed by Hilborn and Walters (1992) for estimating stock size. The three are: (1) scaling catches to abundance using knowledge of absolute catch efficiencies; (2) historical stock reconstruction from fisheries monitoring data; and (3) depletion estimators. The work towards three general approaches here allows flexibility over the direction of future research to assess Welsh king scallop stocks. The remaining method listed by Hilborn and Walters (1992) is mark-recapture or change in ratio methods, which were not considered in this thesis as these approaches assume that marked individuals are able to remix themselves with the unmarked population (Southwood and Henderson 2009) which is an unsuitable assumption for scallops due to their limited movement (Howell and Fraser 1984). Two of the chapters (2 and 3) have also investigated, and contributed to the understanding of, the effect of a unit of fishing effort on the target stock, wider environment and fuel efficiency when areas were repeatedly fished.

Greater understanding of whether catch rates could be scaled to estimate abundance of scallops was obtained by estimating the absolute catch efficiencies of five commercial scallop dredgers fishing nine areas in Chapter 2. This was achieved using a spatial depletion model which quantified the effect of repeatedly fishing these areas on consequent catch rates. This study demonstrated the wide variation in absolute catch efficiencies (0.13 to 0.62) between commercial vessels and that estimates for individual vessels can also vary considerably. This variation highlighted that catch efficiencies are not suitable for scaling commercial scallop catch rates to estimates of absolute abundance without further research. This chapter also investigated whether sediment type, vessel characteristics (such as size, engine power or number of dredges) or vessel practices (such as total swept area of hauls, length of hauls and haul speed) could explain the differences in absolute catch efficiencies between vessels, but ultimately the sample size was not large enough to draw strong conclusions.

In Chapter 4, absolute catch efficiency was also estimated for the research vessel RV Prince Madog using three different historical reconstruction IA stock assessment models. These estimates should be treated with some caution based on the data caveats highlighted in Chapter 4. Each model provided a differing estimate of catch efficiency, length-structured catch efficiency curve, age-structured catch efficiency curve and overall catch efficiency regardless of scallop size or age, and therefore these estimates were not directly comparable between the three models. Either of the structured catch efficiency curves or the unstructured model catch efficiency estimate could be used to scale this research vessel's catches to absolute abundance in the dredge path in the future, or could be incorporated as prior distributions for future analyses to further study research vessel catch efficiency. The unstructured model also estimated the commercial fishery catchability, which is the proportion of the entire stock that was removed with a unit of effort (Arreguin-Sanchez 1996), however, much like commercial vessel catch efficiency, further research of small scale variation in catchability is encouraged before catchability could be used to scale commercial catches to abundance. As with the catch efficiency estimates, the catchability estimate is likely to be useful as a prior distribution for stock assessments in other fisheries.

The median catch efficiency estimates from the age- and length- structured models (0.69 and 0.63, respectively) would be expected to be greater than all those estimated in Chapter 2 (0.13 to 0.62) as the survey dredges have a finer belly ring diameter than the commercial dredges, and because the age- and length- structured model estimates were for only the age(s) or size(s) which the gear caught best. It would be challenging to estimate age- or length- structured catch efficiency curves from catch data alone using the Patch model implemented in Chapter 2, as gear selectivity and catch efficiency are confounded in this situation (Hennen et al 2012). The estimated median catch efficiency from the unstructured model is also not directly comparable to the Chapter 2 estimates because of the differences in dredge specifications and because the unstructured model estimate spanned all ages or sizes of scallops, whereas the Chapter 2 estimates were for scallops ≥ the MLS only.

The three historical reconstruction models implemented in Chapter 4 also each estimated the stock size within the areas open to commercial scallop fishing in ICES statistical rectangle 33E5 across a five year time series. Again, these estimates should be treated with some caution due to the data caveats highlighted in Chapter 4. The spatial depletion model in Chapter 2 was also used to estimate mean king scallop ≥ the MLS densities for nine small areas in close proximity, and these could then be expressed as absolute abundance (≥ the MLS) within these areas. The range of densities between the areas demonstrated that scallop abundance can change considerably over a relatively limited spatial range of similar habitat. The total stock abundance estimates from the age- and length- structured models in Chapter 4 were expressed as densities after division by the area of the assessment area, but these would not be directly comparable to the densities estimated in Chapter 2 because those focused on only scallops ≥ the MLS. However, it is possible to extract only the abundances from those length-classes ≥ MLS from the length-structured model (although not presented in this thesis) and compare densities across the same size range to explore the differences in densities between these open and closed commercial fishing grounds in 2014. This comparison is not made here due to the aforementioned uncertainty in the current length-structured model stock size estimates. It should also be noted that the Chapter 2 densities were estimated for April 2014 and prior to the fishing intensity experiment, and those in Chapter 4 were estimated for the end of the 2014 calendar year. Therefore, the density estimates from Chapter 2 and Chapter 4 are not directly compared here to analyse differences in densities between fished and unfished king scallop beds. This comparison was not an aim of the thesis and the data used from the fishing intensity experiment did not include king scallops < the MLS.

In addition to analysing the effect of a unit of fishing effort on the consequent catch in Chapter 2 using a spatial depletion model, the effect of a unit of fishing effort on environmental efficiency and fuel consumption rate as areas were repeatedly fished was investigated in Chapter 3. It was shown that the relationship between vessel catch efficiency and depletion rate is important for understanding changes in environmental fishing efficiency as areas were repeatedly fished by dredges. In particular, this work demonstrated that a vessel with a catch efficiency greater than the benthic depletion rate would have an increasing environmental impact relative to the target catch as it continued to fish an area. The opposite was also true, that a vessel with a catch efficiency less than the benthic depletion rate would have a decreasing environmental impact relative to the target catch as it continued to fish an area. Fuel efficiency, measured as fuel intensity, was estimated for three commercial vessels as they repeatedly fished areas.

In addition to estimating total stock size and catch efficiencies, several other highly useful life history or fishery parameters were estimated between the stock assessment models in Chapter 4 including annual SSB, annual fishing mortality rates, annual recruitment, length- or age-structured selectivity curves for the fishery, length- or age-structured retention curves from the fishery and biological reference points such as B_{MSY}, F_{MSY} and carrying capacity. These estimates should be treated with some caution due to the highlighted data caveats in Chapter 4. Furthermore, additional fixed parameters were estimated prior to fitting the models including individual growth curve (von Bertalanffy) parameters, size- and age- at-maturity curve parameters and length- and age- weight curve parameters. Many of these parameters would still be useful as prior distributions in other stock assessment analyses. Chapter 4 also highlighted that estimated model structure is an important consideration in stock assessment, as demonstrated by the considerably different estimates produced by the length-structured model compared to the other two models. In addition, this Chapter highlighted that age- and un- structured models can produce similar estimates of stock size and biological reference points.

5.2 Potential data limitations in multiple chapters

The demand for scientific evidence to support sustainable fisheries management with limited data has required fisheries analysts to be creative in their analyses (Maunder and Punt 2013). In all cases, best attempts were made to account for data deficiencies, inconsistencies or errors, or, failing this, approaches were identified that should be considered to analyse such data in the future. The key limitations or benefits of the methods implemented in each previous chapter are discussed there. Here, this section discusses key data limitations which may have affected multiple chapters.

Chapters 2 and 3 both use the same empirical datasets from a fishing intensity experiment, which was not designed to assess catch efficiency, environmental efficiency or fuel efficiency. The analyses in these chapters quantified changes in these variables as areas were repeatedly fished, and were therefore dependent on the overlap between hauls (or depletion pattern). As illustrated in Chapter 2 the depletion patterns were highly variable between vessels, fishing lanes and with increasing cumulative effort. In Chapter 2, this was addressed with a spatial depletion model capable of accounting for this variation in depletion patterns and the resulting findings and estimates should be considered reliable. The depletion patterns were not directly addressed in the analysis of Chapter 3, which may have resulted in bias of estimates. However, as a high amount of effort was applied to the fishing lanes overall depletion patterns were detected (as supported by the estimation of sensible catch efficiency values by the Patch model in Chapter 2) and as specific parameters, such as the slope of a depletion line, were not estimated in this chapter the findings are unlikely to change after an explicit spatial analysis. However, some of the estimated values of RBS, change and fuel intensity at points in time may be erroneous as a consequence.

Accuracy of estimations of landings, catches and fishing mortality is a considerable problem in fisheries assessment, and can occur due to discrepancies in discarding practices, error or illegal catches (Jensen and Vestergaard 2002; Coll et al 2014; Pennino et al 2016). Misreporting of landings or catch data may have affected the data used in this thesis, but remained beyond the scope of this thesis to quantify and account for. Misreporting of landings can result in an underestimation of, or highly imprecise and inaccurate estimations of, fishing mortality rate (Patterson 1998; Jensen and Vestergaard 2002), and therefore the estimated fishing mortality rates in Chapter 4 may be underestimated or inaccurate if considerable landings misreporting occurred. Erroneous catches from the fishing intensity experiment dataset used in Chapters 2 and 3 may have also affected estimates and findings, but every effort was made to ensure any errors were extremely limited as highlighted in these chapters.

5.3 Wider implications

This thesis has estimated a wide range of states, rates and life history parameters corresponding to king scallops and their fishery in Wales and these are of particular benefit to local management for managing the fishery or direct use in future stock assessments or research studies. In addition, many of these estimates will also be useful as prior distributions in stock assessment models or analyses for a wider range of scallop fisheries.

Chapter 2 highlighted that commercial vessel catch efficiency can be highly variable over small spatial scales. This variability indicates that commercial catch rates should not be scaled to estimates of abundance without further research explaining variation in catch efficiencies. This is in agreement with other studies which stated the relationship between catch rates and stock size is too complex to assume catch rates can relate directly to abundance (Hilborn and Walters 1992; Williams et al 2014). The range of estimated commercial vessel catch efficiencies (0.13 to 0.62) was broader than the range estimated by Beukers-Stewart et al (2001) (0.295 to 0.407), for king scallops ≥ 110 mm in shell width. The range estimated in Chapter 2 was also broader than the range from other king scallop fisheries that used similar Newhaven spring-loaded dredges (0.13 to 0.41), although these were not reported to the same size group (Chapman et al 1977; Dare et al 1993; Lambert et al 2014). Therefore, prior distributions of catch efficiency in king scallop stock assessments using catches from commercial vessels fishing with Newhaven dredges should consider the broader range estimated here. Interestingly, there was no evidence that the number of dredges hauled had an effect on catch efficiency in Chapter 2. The research vessel catch efficiency estimated in Chapter 4 was for Newhaven dredges with a different specification to the commercial gear, but was far higher (0.60) than the value estimated for the same vessel and gear by Lambert et al (2014) (0.29). The posterior distribution of this estimate from Chapter 4 (0.25 to 0.93) straddled the estimate by Lambert et al (2014) and highlights that further research is required to determine the catch efficiency of this research vessel.

The initial densities estimated in Chapter 2 were for an area closed to commercial scallop dredging and these densities were within reported ranges of king scallop densities from other closed areas (1 – 85 per 100 m^2) (Table 2.3), although not to the same size category of ≥ 110 mm shell width. The range of estimated densities in Chapter 2 highlighted that king scallop density can vary considerably over small spatial scales (110 km^2 area), and were not shown to be linked to gravel content in the sediment. The densities in Chapter 2 were all higher than those reported by Lambert et al (2014) for the same area and a few months later in the same year (21 per 100 m^2). Lambert et al (2014) reported densities for all sizes of king scallops, and therefore this estimate should be higher than those estimated here. Differences in densities could be due to natural fluctuations or the accuracy of the two different techniques used (videos and depletion estimation). The broad range of density estimates for closed areas from other studies and those estimated here reinforce the need for annual surveys to assess changes in abundance across small spatial scales.

The comparison of three IA stock assessment models which each estimated stock size with different stock structure highlighted that choice of stock assessment model structure is complex and likely case dependent. Both the age- and un- structured models produced reasonable and sensible estimates of stock size, which contradicts studies which have found unstructured models incapable of doing this (Townsend 1986; Bjorndal and Brasao 2006; Tahvonen 2008). Similarly, the implemented unstructured model had high goodness-of-fit between estimated and observed commercial data, despite being applied over only five years, which is in disagreement with other studies which have reported poor fits between observations and estimates from unstructured models (Massey et al 2006; Jonsen et al 2009). The ability of an unstructured model to perform similarly to an age-structured model is in agreement with other studies which have shown unstructured models can estimate key metrics as well as age-structured models (Ludwig and Walters 1985; 1989; Moxnes 2005). In those studies the key metrics were optimal effort and economic revenue, and therefore different to the key metrics analysed here. This work showed that unstructured models, commonly known as production, surplus-production or biomass dynamic models, can be useful tools for estimating stock size in fisheries.

The critical relationship between vessel catch efficiency and depletion rate is important for understanding changes in environmental fishing efficiency as areas are repeatedly fished by towed gears (Chapter 3). This relationship indicated that lightly fishing areas is more environmentally efficient for highly efficient vessels as there will be less to catch on consequent hauls relative to the environmental impact of consequent hauls. In contrast, the effect of less efficient vessels repeatedly fishing an area is less problematic as these vessels will still return reasonable catches relative to the amount of the environmental impact caused by consequent hauls. This finding is important for environmentally focussed management plans looking to balance trade-offs between maximising profit through catches and reducing the environmental impact of the fishery through effort limitations, as discussed later. Potential effort limits have also been discussed by Lambert et al (2017), who analysed recovery four months after the experiment studied in Chapters 2 and 3 and found that fishing intensities > 6 on seabed communities was closest to the magnitude of natural disturbance in the area. This implied that all the fishing conducted during the experiment in Chapters 2 and 3 had a lesser effect than natural disturbances, although Lambert et al (2017) discuss a precautionary approach towards identifying a seabed impact effort threshold.

The estimations of fuel intensities of three commercial vessels in Chapter 3 demonstrated that king scallop dredge fuel intensity here was lower than median estimates from a global analysis of dredge and mollusc fisheries (Parker and Tyedmers 2015). Lower fuel intensity indicates less fuel is required to catch a tonne of scallops and therefore the fishing is more fuel efficient. The primary reason for this is likely to be high density scallop sites chosen for this experiment, and these values demonstrate that scallop fishing in such high density areas is relatively fuel efficient compared to the global averages.

5.4 Implications for management

The evidence from the two best performing stock assessment models in Chapter 4 showed that the stock size in the open fishing grounds of ICES statistical rectangle 33E5 decreased with time between 2012 and 2016, and landings of scallops by UK vessels in to Welsh ports have also declined from 2012 onwards (Figure 1.4) which may indicate further decline in stock sizes. Therefore, management should focus on reducing the fishing mortality rate of scallops in Welsh waters to attempt to prevent further stock decline. Two key strategies for reducing fishing mortality rate are to set a catch limit or to set effort limits for vessels targeting king scallops. Either of these strategies could be implemented across large regions of Welsh waters (such as Cardigan Bay) or may be applied to small areas in a rotational fashion.

Catch limits could be set as an annual TAC for the Cardigan Bay fishery assessed in Chapter 4. Setting a TAC has been done in scallop fisheries such as the Patagonian scallop (Pottinger et al 2006), the USA weathervane scallop *(*NPFMC 2014), East Canada sea scallop fishery (Caddy et al 2010; DFO 2013), US sea scallop (Aldous et al 2013), IoM queen scallop (Andrews et al 2010) New Zealand scallop (Cryer 2001a; Williams et al 2010; Twist et al 2015) and the Iceland scallop (ICES 2013) fisheries. The three stock assessment models applied in Chapter 4 each produced an estimate of MSY which could be used to set an annual catch limit for this fishery. However, these estimates should be treated with caution due to the data caveats highlighted in Chapter 4 and because it is often considered too risky for management to set catch limits at estimates of MSY (Maunder 2008). Consequently MSY and B_{MSY} have recently been considered as limit reference points to indicate when a fishery risks becoming unsustainable rather than target reference points (Maunder 2008). Therefore, the recommended catch limit should be precautionary. The age- and un-structured model median MSY estimates were approximately 364 tonnes and 498 tonnes, respectively. However due to model estimate uncertainty and the data caveats, a TAC between the lower 95% prediction intervals of each of the age- and un-structured model estimated MSY (49 to 126 tonnes) could be set for the assessment area. The length-structured model outputs are not considered here due to it being the worst performing model. Additionally, the TAC should only be increased in the future when the long-term stock size is also increasing with time because this avoids adjustment based on natural annual fluctuations, and this approach is implemented in the IoM queen scallop fishery (Andrews et al 2010).

Catch rates from the fishery could be used to assess whether the TAC is likely to be met, over- or under- shot in a season, as is done in the East Canada sea scallop and IoM queen scallop fisheries (Andrews et al 2010; Caddy et al 2010; DFO 2013). If TACs are overshot then fishing seasons could be closed early or the overshot amount deducted from the following year's TAC (Andrews et al 2010). The TACs could be implemented as ITQs, which is done in New Zealand scallop fisheries (Williams et al 2010), and would allow fishers to sell or trade unused or unwanted quota to other fishers (Copes and Charles 2004). After scallop stock assessments are conducted for other parts of Welsh waters, individual TACs could be assigned to different regions and this is an approach that has been implemented in the US sea scallop fishery (Aldous et al 2013). Alternatively, catch limits may not be based on the outputs from these models due to the highlighted data caveats and these models may instead serve as an example of appropriate methodology for stock assessment once they can be applied with less of these caveats.

The data requirements of the best performing models (age- or un- structured) can drive future data collection. The age-structured model had greater data requirements, required more fixed parameters, estimated more parameters and was generally more complex than the unstructured model, but as a consequence provided greater detail and was capable of estimating additional pieces of information such as recruitment and SSB. The age-structured model was also capable of estimating age-structured fishery selectivity and retention curves and age-structured survey catch efficiency. These estimates will become more reliable and be less dependent on prior distributions when more informative data are available, as has been shown with recent applications of the age-structured model to the IoM king scallop fishery (not displayed here). In contrast, the unstructured model estimated far less parameters than the age-structured model, estimated fishery catchability and was not dependent on potentially erroneous aging of king scallops, but required the effort data corresponding to the catches. The trade-off between data requirements, complexity and outputs is a subject for consideration by future stock assessment analysts.

Addressing the aforementioned areas required to improve the availability and accuracy of data, and the accuracy of the analytical methodology, are likely to improve the reliability of the estimates from the stock assessment models. The key data collection improvements are increasing the time series of commercial data available, developing systems so that these can be reported at finer spatial scales in line with local MLS management and accounting for neighbouring closed areas in stock assessment models (Punt and Methot 2004; Field et al 2006; Pinchin and Wilberg 2012). In particular, if landings were reported to finer spatial scale then these models could be applied to many other areas around the Welsh coast to estimate king scallop stock sizes.

However, enforcing catch limits upon the Cardigan Bay stock would have considerable management challenges. There is currently no licencing for the assessment area and therefore no way to control the number of vessels, or how much they each land. Implementing a licencing system would be challenging as an agreement would need to be formed between both the EU and Wales so that the licencing would apply to both Welsh waters and EU waters (as both are in the assessment area). In addition, it is also likely to be challenging to determine whether landings from the Cardigan Bay stock were obtained from the assessment area or otherwise under the current reporting system and as a result catches may be biased. However, the conversion of catch limits to an effort-based approach may be more appropriate for this fishery in an attempt to limit fishing effort further.

Swept area is recommended here for quantifying scallop dredge effort because it accounts for the number of dredges hauled and can be used to easily standardise catches and environmental impact. Many scallop fisheries regulate effort through temporal restrictions (Hervas et al 2011; ICES 2013; Tindall et al 2016). However, it is recommended that effort is regulated by swept area in the Welsh king scallop fishery as this would allow for direct quantification of amount of seabed impacted by each haul. Vessel monitoring systems are available to monitor, in real time, the spatial patterns of vessels fishing within a given area (Wallace et al 2015), and there have been advances in technology which permit real time catch and landings reporting (Little et al 2015). Therefore, the tools are available to monitor the efficiency of fishing and incorporate this in to management as is already done in multiple fisheries throughout the world (Little et al 2015).

An effort based approach could be highly effective in a rotational management fashion, where areas are opened, fished and then closed once particular thresholds are met. Rotational closure of areas within the fishery could allow for the recovery of areas and protection of juveniles whilst fishing still persists in other areas (Stewart and Howarth 2016). Rotational management has been used in multiple scallop fisheries (Holmes et al 2013; Williams et al 2014; Akroyd et al 2015). After rotational management was implemented in the US sea scallop fishery catch rates increased considerably in some areas (0.8 kg/tow to 9.7 kg/tow between 1997 and 2000), there was evidence of overall greater mean weights of landed scallops and greater larvae export was detected (Hart 2003; Hart and Rago 2006; Aldous et al 2013). The use of rotational areas has also been considered effective in protecting the ecosystem as well as protecting sea scallops in this fishery (Aldous et al 2013). Effort-based rotational management has the possibility to work in Cardigan Bay where closed areas had high densities of commercially sized king scallops in 2014 (Chapter 2) and consequent fishery-independent surveys indicate high densities existed in these areas in 2019 (Delargy et al 2019). The threshold for opening and closing areas could be based on catch rates like the Shetland king scallop fishery which can be closed if LPUE rates drop below a pre-defined level (23 marketable king scallops per hour per dredge) (Tindall et al 2016). This approach would also require that landings were reported on a finer spatial scale, as previously mentioned. The threshold could also incorporate the findings from Chapter 3 and consider the catch efficiencies of vessels repeatedly fishing small areas in an attempt to reduce the amount of environmental impact per tonne of king scallops landed. This would involve quantifying and classifying vessels by low, medium or high catch efficiencies and limiting their effort accordingly, with the most efficient vessels being able to apply the least amount of effort. This is an example of a trade-off between target species catch efficiency and reducing environmental impacts, but could also be extend further to include other factors in the trade-off such as fuel efficiency.

The effort-based approach is likely to better control the environmental impacts of the fishery than a TAC approach, especially if a strategy directly incorporating environmental fishing efficiency is incorporated as an effort threshold for areas. A TAC does not determine how much effort is employed and therefore the environmental impacts of catching a given TAC are far more challenging to quantify than an effort-based approach. Therefore, the effort-based approach is the recommended management strategy for the Welsh king scallop fishery.

5.5 Data gaps and future work

The evidence required to implement the suggested management strategies is dependent on accurate estimates of stock size or careful understanding of the effects of a unit of effort on the target species and wider environment. The techniques used to study these would each benefit from future research as outlined here.

To continue to implement the IA stock assessment models from Chapter 4 in the future, several key data gaps should be addressed in addition to improving the temporal length and spatial scale of the datasets. In particular, research to determine the parameters of any of the three selectivity curves estimated in each of the length- and age-structured models would likely result in improved overall model performance. Experiments to define the selectivity of both landings and discards in commercial dredges and the survey dredges could be conducted by comparison of catch rates from multiple gear types (e.g. Hamley and Regier 1973; Millar 1992). Alternatively, tag and recapture studies could also be employed to achieve this (e.g. Anganuzzi et al 1994; Myers and Hoenig 1996). Absolute catch efficiency, required for all three stock assessment models, could alternatively be estimated by a depletion study (Beukers-Stewart et al 2001; Rago et al 2006), with divers (Beukers-Stewart et al 2001; Fifas et al 2004), using optical methods (Lambert et al 2014; Miller et al 2019), by mark-recapture (Dickie 1955) or by dredging over known abundance on seeded grounds (McLoughlin et al 1991).

The natural mortality rate could be estimated from tag data (Hearn et al 1998; Frusher and Hoenig 2001; Latour et al 2003) or predictions from life history, such as growth parameters (Chen and Watanabe 1989; Jensen 1996; Lorenzen 1996). To account for neighbouring closed areas the migration rate of the stock (both larvae and adults) between open and closed areas would need to be quantified by a research study or estimated within the stock assessment models (Pinchin and Wilberg 2012). Similarly, it is also important to better define the connectivity between scallop beds within Wales to help define stock assessment units. Such research could include further genetic or biophysical larval dispersal modelling studies (Chow et al 1997; James et al 2002; Hold et al in press). Broadening the range of commercial vessels sampled by scientific observers would allow for a better estimate of the annual discarding rate. This is essential for estimating the amount of king scallops which are returned to the sea after capture.

Modelling additional observed data would also be useful for future model development to account for further uncertainty in estimates (e.g. Methot and Wetzel 2013). For example, observed fishing effort data can be modelled to help tune fishing mortality to the correct trend and magnitude in each of the length- and age- structured models (Xiao 1998). Tagging data could be obtained and modelled to help estimate growth, address parameter confounding and can be modelled as a secondary set of survey data to better estimate abundance (Punt et al 2013; Hillary and Eveson 2015). Environmental data could be modelled if a relationship with stock recruitment was defined, or environmental variables may be directly linked to stock size (e.g. Haltuch and Punt 2011). King scallop recruitment has been shown to be affected by mean spring sea temperature, availability and quality of larval settlement habitat and chemicals used in the netting of salmon farms (Minchin et al 1987; Shephard et al 2009; Howarth et al 2011). In addition, other scallop fisheries have reported a wider range of factors affecting recruitment including predator abundance, presence of invasive species, algal blooms, density of the spawning scallop stock, hydrodynamic conditions, disease and physical disturbance (Summerson and Peterson 1990; Hart 2006; Morris et al 2009). Therefore, any study which can quantify effort, implement tagging research or investigate relationships between environmental variables and stock size or recruitment would be useful for the improvement of stock assessment of this fishery.

An alternative approach for estimating stock size investigated in this thesis is to scale catches to abundance using knowledge of vessel catch efficiencies (Hilborn and Walters 1992). The remaining abundances within dredge paths can then be extrapolated to estimate abundance in areas between dredge paths using geostatistical techniques (Petitgas 1996). The estimated catch efficiencies of five commercial vessels fishing nine small areas (Chapter 2) highlighted that greater understanding is required before this approach could produce reliable estimates of abundance, due to the high variability in catch efficiency estimates. Vessel catch efficiency can be further studied using a variety of methods such as optical methods or dives pre- or post-dredging (Caddy 1968; 1971; Beukers-Stewart et al 2001; Fifas et al 2004; Lambert et al 2014; Miller et al 2019), mark-recapture (Dickie 1955), index-removal (Gedamke et al 2005), depletion (Chapter 2; Beukers-Stewart et al 2001; Rago et al 2006) and dredging over known abundance on seeded grounds (McLoughlin et al 1991). Many of these methods could be implemented in controlled studies designed to investigate the effects of various factors such as habitat type, vessel characteristics and fishing practices in isolation.

Both the IA stock assessment models implemented in Chapter 2 and directly scaling catches to abundance either require direct knowledge of catch efficiency or make assumptions about catch efficiency. Alternatively, optical methods can be used to directly sample scallop stocks and sidestep the need to estimate catch efficiency of towed gears altogether. Capture efficiency (equivalent of catch efficiency) of optical methods can be close to one, which is considerably better than most towed gears, and this can result in more accurate estimates of abundance (Stokesbury 2002). Absolute abundance of sea scallops has been routinely estimated using optical methods in the US, with the absolute abundance of the total survey area estimated using the mean density of sea scallops from video samples taken across small areas (Stokesbury 2002; Stokesbury et al 2004). This camera system is now able to measure shell height of the scallops, detect greater numbers of juvenile sea scallops, and the absolute abundance estimate accounts for both the selectivity and capture efficiency of the method (Carey and Stokesbury 2011; Bethoney and Stokesbury 2018). Scallops in this fishery have also been sampled using an AUV fitted with a camera which is capable of estimating scallop abundance and measuring shell height (Walker et al 2016). AUVs have also been successful at estimating scallop abundance in Iceland scallop fisheries (Singh et al 2013) and may be suitable for estimating shell size with future research (Singh et al 2014). Furthermore, AUVs can also be used to detect dredge scars on the seabed indicative of fishing effort (Walker et al 2016). Therefore, scientific surveys may wish to invest in either optical system to monitor king scallop stocks in Wales, which would also considerably reduce the environmental impacts of stock assessment surveys.

However, knowledge of dredge catch efficiency remains important whilst it is a capture method in the commercial fishery. The proposed effort-based rotational management strategy takes account of the trade-off between catch efficiency and environmental impacts and would benefit from further quantification of both vessel catch efficiency for scallops and the benthic depletion rates by dredges across habitats in the fishery. In addition to the aforementioned methods for studying catch efficiency, benthic depletion rates could be further studied by before-after-control-impact towed gear experiments (e.g. Hiddink et al 2006; Lambert et al 2017).

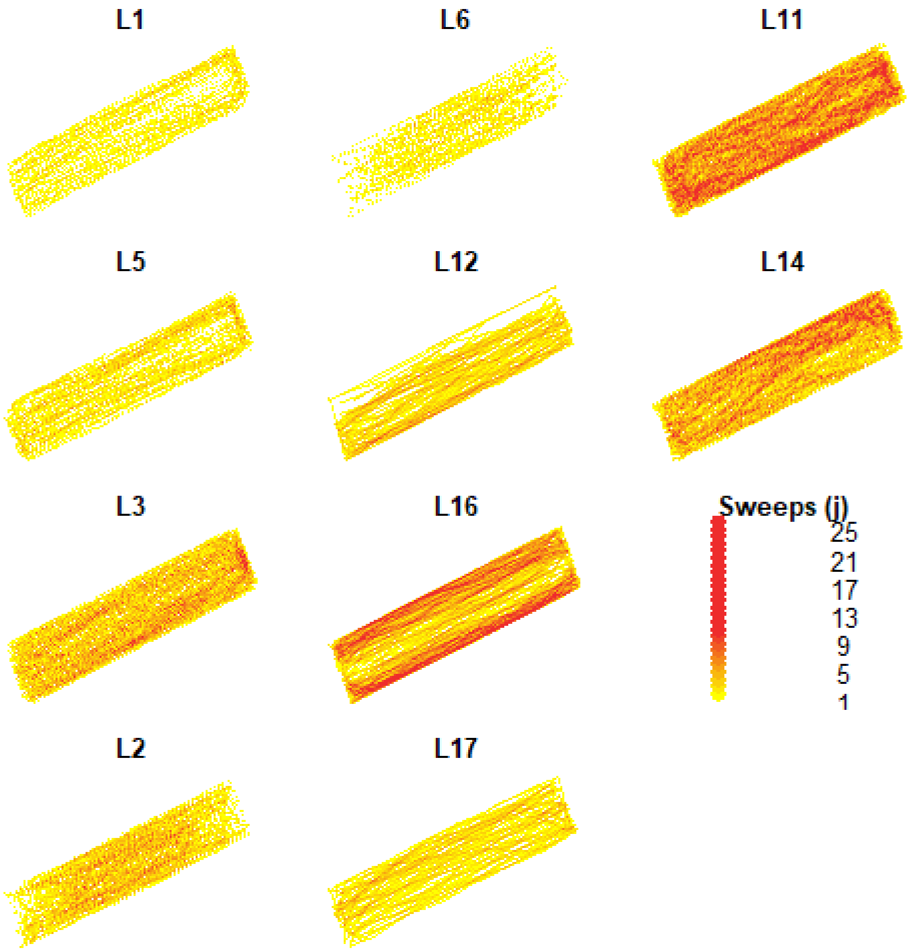
5.6 Conclusions

This research developed and implemented methodologies to estimate key pieces of evidence that could support strategies for the sustainable management of Welsh king scallop populations. The key pieces of evidence were multiple estimates of absolute stock size with time and the MSY of a key Welsh king scallop stock (Chapter 4) and the relationship between the catch efficiency and benthic depletion rates when areas were repeatedly fished (Chapter 3). These key pieces of evidence allowed the proposal of strategies to attempt to manage the Welsh scallop fishery sustainably. In addition, this research directly estimated absolute abundance of king scallop populations in small areas, demonstrating another useful technique for estimating absolute abundance, and also estimated catch efficiencies of multiple commercial scallop vessels (both Chapter 2). The research of vessel catch efficiencies serves as another technique for estimating absolute abundance, through the scaling of catch rates, but this technique is not advised until further research is conducted. Collectively these three chapters achieved the two key aims of the thesis, to implement techniques to estimate absolute scallop abundance and investigate the effect of a unit of fishing effort on the target species and the environment.

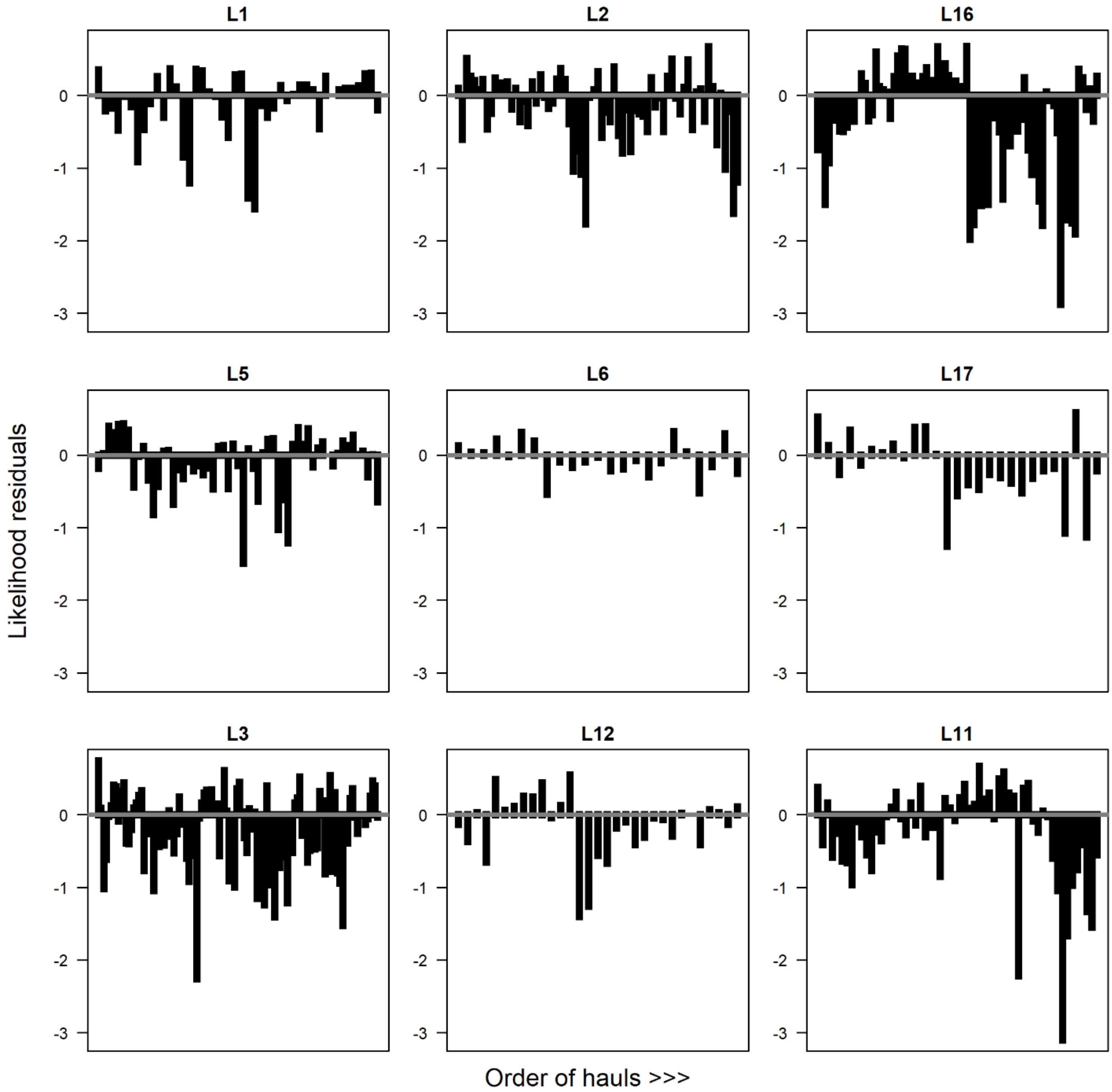
In addition, a wide range of further king scallop life history and fishery parameters have been estimated in this thesis including, the Cardigan Bay stock annual SSB, annual fishing mortality rate, annual recruitment, biological reference points, research vessel catch efficiency (overall, age-structured and length-structured), age- and length- structured fishery selectivity and discard retention curves, fishery catchability, von Bertalanffy individual growth parameters, age- and length- weight curves, age- and length- at-maturity curves and fuel intensities of three commercial scallop vessel as they repeatedly fished areas. The vast majority of these parameters were estimated for the first time for the Cardigan Bay fishery assessed in Chapter 4, and can serve as prior distributions for parameters in future stock assessments of Welsh and other king scallop stocks.

Furthermore, this thesis also demonstrated that vessel catch efficiencies can vary considerably over small spatial scales, both between vessels and estimates for single vessels. Similarly, scallop densities can also vary considerably over small spatial scales and, in this case, the differences in densities were not driven by the sediment type. This thesis also demonstrated that vessels using towed bottom gears with a higher catch efficiency will cause an increasing environmental impact relative to the amount of target catch as they repeatedly fish an area. Furthermore, king scallop dredging was shown to have greater fuel efficiency than the global average for dredge and mollusc fisheries. Lastly, this thesis demonstrated the importance of carefully considering estimated stock structure in historical reconstruction stock assessment models and that unstructured models can produce similar estimates of stock status to age-structured alternatives.

APPENDIX



Appendix figure 1: The number of times 10 cm apart points were swept in each of the fishing lanes from the fishing intensity experiment in Cardigan Bay. The number of times swept is coloured as indicated in the figure legend.



Appendix Figure 2: Standardised residuals from the likelihood of each Patch model fit reflecting the difference between observed and estimated catches. Standardised residuals were calculated per haul as $\frac{obs-est}{obs}$, which means a negative standardised residual results from an observed catch less than the estimated catch.

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