

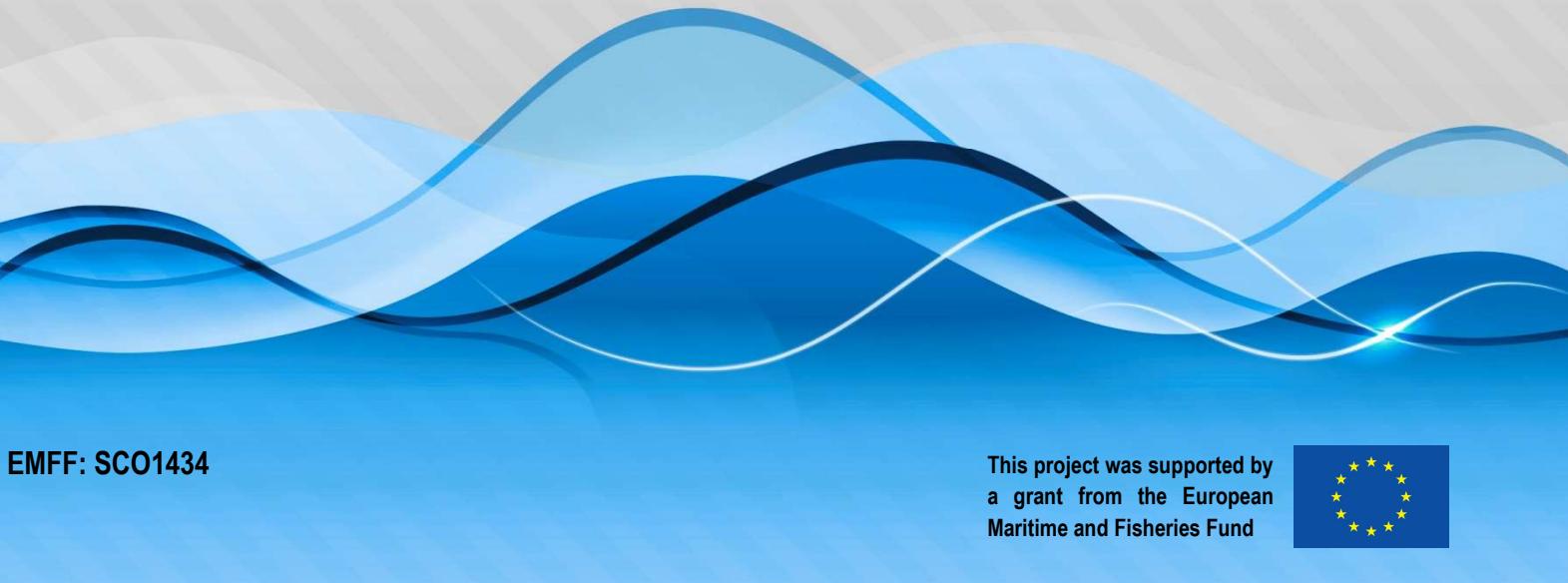
SIFIDS

Scottish Inshore Fisheries
Integrated Data System

Work Package 1 Final Report

Review and Optimisation of Shellfish Data Collection
Strategies for Scottish Inshore Waters.

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EXECUTIVE SUMMARY

i) Background

The collection of additional data to facilitate fisheries management has been identified as a priority at the national level via the Scottish Inshore Fisheries Strategy, and at the local level in the management plans of Regional Inshore Fisheries Groups. Data collection implemented by industry offers a potentially cost effective means by which to provide additional information to enhance current stock assessment programmes, and to produce empirical indicators to inform fisheries management. The fundamental driver for data collection should be the purpose for which it is required; however, the regionalisation of fisheries management and increased, and often competing, demands, on our marine space mean that there are many potential uses for industry derived data.

This report presents the findings of a single work package in the wider prototypic Scottish Inshore Fisheries Integrated Data System (SIFIDS) project; looking at ways in which inshore fisheries data collection can be improved on. The propose of this work package was to review and evaluate current inshore (shellfish) fisheries data collection and stock assessments in order to determine where it might be possible for industry derived data collection to provide a positive contribution. For the purposes of this work package the focus was limited to brown crab, lobsters, and scallops.

The information contained within this report is intended to inform Marine Scotland at both Science and Policy levels, Regional Inshore Fisheries Groups, and further work packages in the SIFIDS project. The report contains a review of the current data collection and stock assessment programmes; this is followed by analyses of available data in order to determine where additional sampling would be beneficial. The report also contains information on possible mechanisms by which fisher led data collection could be carried out, and a process for the design of sampling protocols involving industry.

The analysis provided in this report, and contained within the technical appendices, is very detailed and is designed to provide an indication of where industry derived data could be utilised by scientists and data managers within the existing stock assessment programme. There are a great deal of data that are collected as part of the stock assessment programme. It was not possible, within the time constraints of this project, to review all of the data for each of the species in question. The report therefore focuses on a few specific areas including the potential for enhancing length frequency data for use in crustacean stock assessments, and the use of daily landings information as a proxy for landings per unit effort (LPUE).

ii) Data and Stock Assessment

The data collected on Scottish inshore fisheries are currently provided via logbooks, through onshore catch sampling, and via scientific surveys. Information on effort and precise location of fishing activity has only been collected since the introduction of the FISH1 form in 2016. Prior to that, the spatial resolution of data was at the level of ICES statistical rectangles, with stock assessments being reported via set assessment areas, incorporating multiple ICES rectangles.

The analyses carried out within this work package have shown that there are regional differences in the quality of data being collected for the assessments of those shellfish stocks

reviewed. Areas where additional data collection by industry could enhance those data sets have been identified, and the level of additional sampling quantified.

It is implicit in the introduction of new data collection technologies that more sampling is better. The results presented here suggest that qualification of what is meant by “more” is required. This may or may not be relevant to a given technology, depending on cost and mode of implementation. For example, camera and/or video technology can be expensive, and may only be introduced on a few vessels with defined technical requirements.

Appropriate sampling intensity was investigated: an examination of the crustacean length frequency data showed that a reduction in the error variance associated with the data can be obtained by an increase in the sample size per trip i.e. the number of individuals measured from a vessel on a particular day. This effect is true only up to a certain point when it then becomes necessary to increase the number of trips sampled. Provided the sample size per trip is large enough, the additional number of trips which would need to be sampled is relatively modest.

An important result detailed in Technical Appendix 3 is that instances of low sample size in the historic record increase the mean weighted coefficient of variation (MWCV) substantially for both lobster and crab. The causes of low sample size per trip need to be properly understood before clearly recommending specific remediation. We do not know, for example, whether the occurrence of low sample size is due to low catches, so that even though the entire catch was sampled, sample size is low; or if it is due to low proportions of species in catches, so that the random sample that was drawn contained a small number of animals for the species of interest. Remediation is different depending on which is the determining factor. If low catches, then in order to mitigate this problem consideration of sampling vessels with larger catches must be contemplated. If low proportions of required species, then oversampling of species which do not show sufficient sample size in the usual random sample that is drawn is required. If there is no possibility to mitigate either, then the only way to achieve a desired level of precision for catch length frequency estimates is to increase the number of trips that are sampled.

The nature of the fleet itself presents some challenges when proposing a fisher led data collection programme (e.g. sentinel vessels). From a practical point of view, the vessels in the inshore fleet are wide ranging in their size and fishing capacity. Some vessels may not have sufficient deck and wheelhouse space in which to locate technological data collection methods, some smaller vessels may have lower catches, which would not provide a large enough sample size for the data to be included in stock assessment processes. That said, only sampling larger vessels in the fleet may provide more robust data sets for stock assessment purposes, but may not provide an accurate overview of the activity of the fleet upon which broader management measures might be based (e.g. spatial or temporal management).

A proposed method for optimising sampling across a range of options is proposed. Use of a Length Proportion Variance Calculator (LVPC) is described to assess the statistical value of different sampling designs in relation to cost and logistical feasibility. This approach, based on the outputs of the analyses contained in this report, has the benefit of being able to be modified to incorporate different sampling approaches so they can be assessed on the basis

of cost, logistic feasibility and statistical merits. A flexible approach to sampling may also be appropriate in order to tailor regional data collection solutions relative to specific management goals.

Current stock assessment is facilitated via Length Cohort Analysis (LCA) for crustaceans and Time Series Analysis (TSA) for scallops. Length Cohort Analysis has the well-known limitation that it assumes the fishery is being exploited under equilibrium conditions. This condition is likely to be met when the level of fishing mortality (and hence effort) and the level of recruitment has remained unchanged over a long period of time. The possible existence of disequilibrium conditions in crab and lobster fisheries is considered here to be the most significant potential source of bias for LCA based estimates of fishing mortality. Some possible alternative stock assessment methods are suggested for application to crab and lobster stocks, namely the use of length based dynamic methods in which the growth process is explicitly modelled. Although such methods can accommodate a wide variety of data types that may become available in the future, they should only actually be used in management decision making if they incorporate indices of abundance such as Catch per Unit Effort (CPUE), or a survey abundance index. If the vision for the future is to explicitly model resource dynamics and incorporate the results from such dynamic modelling approach into management, then for crab and lobster we advise the use of dynamic length-based stock assessment models using catch-at-length and CPUE data inputs into the stock assessments.

TSA is considered to be a sound approach which is adequate for management purposes and it is rated above alternative approaches taken in other countries. A disadvantage with TSA compared to other general integrated stock assessment approaches (IA) used elsewhere, is that the methodology and the software is less accessible than IA. The result is that the skills for application of TSA are less wide-spread. This is a potential limitation for recruiting the necessary skills for stock assessment analyses. For this reason the additional use of IA methods is recommended, preferably developed from the ground up. It would be very useful to compare the results obtained using IA with those from TSA.

In the absence of a historical time series of effort data, an analysis of information from Shetland (for which local effort data are available via the Shetland Shellfish Management Organisation) indicated that daily landings provided a very useful proxy for Landings Per Unit Effort (LPUE). A contributing factor to the utility of this approach in the case of Shetland is that analysis results presented here indicate that there has been little increase in effort per vessel per day over time. Daily catches could be utilised to determine trends in potential stock abundance in other areas, provided there were only very small changes in effort over time, as has been the case in Shetland. Whether this is the case has not been verified in this report.

iii) Discussion

There is currently a disconnect between the data collection being carried out for stock assessment purposes and the data required at the Regional Inshore Fisheries Group (RIFG) level for the management of fisheries. The devolution of fisheries management RIFGs has resulted in a need for fisheries data that are more relevant to management decision making. Data collection facilitated by fishers (e.g. through automated systems on board a reference fleet) provides a mechanism by which this data can be collected. There may well be no "one size fits all" sampling programme that can be implemented at the national level to suit all local and regional management requirements. There is however, considerable potential for industry

derived data to make a significant contribution to both the stock assessments carried out by Marine Scotland Science, and also in the provision of valuable time series of data which can be utilised in fisheries management and in the development of indicators and reference points. A recommendation of this report is that Marine Scotland work closely with RIFGs to determine priorities at the regional level. These can then be used to devise regionally appropriate sampling protocols, which can provide data that are suitable both for the stock assessment programme, and also to address management aims.

A significant drawback of the current data management system (including biological data collected by Marine Scotland Science and fisheries data collected via Marine Scotland Compliance) is that information is not readily available for any management requirements which may fall outside the national stock assessment programme (e.g. local fisheries management). Effective management for industry produced data will need to be a consideration for any future programmes. This is to ensure that data are available to facilitate effective management in appropriate timescales. A further important consideration is that any new data sets are compatible with those collected through the existing national programme in order to add value to existing data and provide historical context for new data collected.

It is important to recognise that data collected for the purposes of stock assessment can also have additional value in fisheries management decision making, and wider marine management (e.g. Marine Planning) should it be readily available for this purpose. It is a recommendation of this report that effective data management and communication mechanisms be put in place to ensure best use can be made of data supplied by industry. Early identification of the key assessment and management requirements for the data should be a priority, as the information required for differing management processes may require data at differing resolutions. For example, when collecting biological data for inclusion in stock assessments, the selection process for vessels is likely to be more critical to the quality of the data than the number of vessels, however; data collection for the provision of spatial data within the marine planning process may require detailed spatial information from many, or all, vessels. Designing a data collection programme which is versatile and cognisant of the varying data requirements will be important for ensuring quality data streams and for maintaining industry engagement through the production of useful outputs.

iv) Possible Next Steps

It is important to make a clear distinction between the data required in order to improve on the current stock assessment programme, and the potential for additional data to be generated for use in local fisheries or marine management. Data collected by industry during their normal fishing practices has the ability to deliver both. In this work package, we have identified a framework and process which could be utilised in the design of an industry led data collection programme, a clear next step would be to test the operation of such a process within a defined area.

Practical aims for a pilot project could examine the process of engaging a range of vessels within an area, and examine the logistics of sampling from a range of different vessel sizes and operations. For example vessels to be sampled representing two scenarios 1) a minimum number of vessels with a larger catch which could provide the quality of data required to reduce within trip variance for stock assessments and 2) a wider range of vessels to ensure that the sampling is representative of the entire fishery. Comparing the data between these two

different approaches would allow a quantification of any potential sampling bias and would allow investigation of the practical aspects of vessels selection and equipment fitting. A pilot would also be able to investigate appropriate mechanisms for industry engagement. Aspects of data management could also be examined, e.g. what volume of data is produced by the technologies being proposed in subsequent work packages; how much of this is required for analyses (is subsampling required) and, what are the resource constraints in providing management outputs?

It is critically important to the success of any pilot project, or wider programme, that:

- Fishers are consulted and involved from the outset,
- Effective Mechanisms for consultation and feedback between fishers and scientists are put in place,
- Appropriate data management and reporting systems are developed to meet management needs, including timescales and spatial resolution.

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GLOSSARY OF TERMS

ACL	Allowable Catch Limit
ADMB	AD Model Builder
AIS	Automatic Identification System
CAL	Catch-At-Length
CASA	Catch-At-Size Analysis
CASAL	C++ Algorithmic Stock Assessment Laboratory
CPUE	Catch Per Unit Effort
CV	Coefficient of Variation
DDM	Dynamic Data Manager
DST	Data Storage Tag
EFF	European Fisheries Fund
EM	Electronic Monitoring
ETP	Endangered Threatened or Protected
FAO	Food and Agriculture Organization
FIN	Fisheries Information Network
FMD	Fisheries Management Database
GES	Good Environmental Status
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
GLMER	Generalized Linear Mixed-Effects Models
IA	Integrated Analysis
IQ	Individual Quota
iVMS	inshore Vessel Monitoring System
LCA	Length Cohort Analysis
LPUE	Landings Per Unit Effort
MLS	Minimum Landing Size
MINQUE	Minimum Norm Quadratic Unbiased Estimation
MSComp	Marine Scotland Compliance
MSE	Management Strategy Evaluation
MSFD	Marine Strategy Framework Directive
MSS	Marine Scotland Science
MSY	Maximum Sustainable Yield
MWCV	Mean Weighted Coefficient of Variation
NAG	Numerical Algorithms Group
NOAA	National Oceanic and Atmospheric Administration
NOK	Norwegian Krone
ORCS	Only Reliable Catch Stocks
PSA	Productivity-Susceptibility Analysis
RFID	Radio Frequency Identification Device
RIFG	Regional Inshore Fisheries Group
RY	Replacement Yield
SAIP	Stock Assessment Improvement Plan
SSB	Spawning Stock Biomass
SSMO	Shetland Shellfish Management Organisation
TAC	Total Allowable Catch
TAE	Total Allowable Effort
TSA	Time Series Analysis

UDF	User Defined Function
VCA	Variance Component Analyses
VDRS	Voice Data Recording System
VMS	Vessel Monitoring System
VPA	Virtual Population Analysis

1 INTRODUCTION

The collection and analysis of fisheries data for use in fisheries management is absolutely essential. It is also key that such data be collected in a representative and effective way to provide the quality and scale of information needed to facilitate management decision making. Inshore (shellfish) fisheries are traditionally considered to be data poor or data limited when compared with the whitefish and pelagic sectors. This means that it may not always be possible to carry out analytical stock assessments, and fisheries managers are left with a lack of information on which to deliver biological, environmental, and socio-economic objectives. Moving fisheries from a data limited situation to one where there are sufficient data should always be a priority (e.g. Bentley, 2015; Jardim, *et al.*, 2015). In an ideal situation, fisheries monitoring should be developed with clear links to well defined management objectives, and should be established within a system of simulation modelling in order to determine the value of the data.

In the Scottish context, shellfish fisheries data collection has been carried out in order to facilitate stock assessments. It is recognised, however, that these assessments are not comprehensive and that there are additional data requirements which would enable more effective management of these important fisheries resources, ensuring sustainability for remote and rural communities, and increasing the economic value of the sector.

A European Maritime and Fisheries Funded project titled “Scottish Inshore Fisheries Integrated Data System” has been developed and aims to “support the development of a more sustainable, profitable, and well managed inshore fisheries sector by modernising the management of inshore fisheries”. In order to address these aims, the project was broken down into 12 work packages:

- WP1 Review and optimisation of shellfish data collection strategies for Scottish Inshore waters**
- WP2A Development and pilot deployment of an autonomous fisheries data harvesting system
- WP2B Investigation into the availability and adaptability of novel technological approaches to data collection
- WP3 Development of a novel, automated mechanism for the collection of scallop stock data
- WP4 Assessment of socio-economic and cultural characteristics of the Scottish Inshore fishery
- WP5 Capture and incorporation of experiential fisheries data
- WP6 Development of a pilot relational data resource for the collation and interpretation of inshore fisheries data
- WP7 Engagement with inshore sector to promote and inform
- WP8A Supply of on-board observers
- WP8B Identifying fishing activities and their associated drivers
- WP9 Assessment and consultation regarding options for the ‘Real World’ implementation of the project
- WP10 Project coordination

This report is the outcome of Work Package 1.

The overall objective of Work Package 1 is to review current practice in shellfish data collection and stock assessment in order to provide objective information on optimisation using industry derived data. With the requested focus of the work on brown crab (*Cancer pagurus*), European lobster (*Homarus gammarus*), and king scallops (*Pecten maximus*) as three commercially exploited species specified within the UK Programme of Measures for the Marine Strategy Framework Directive (MSFD). Specific emphasis was placed on examining the potential for a reference fleet approach using selected vessels from these fisheries to collect additional data which would feed into and enhance current data collection and stock assessment processes. For the purposes of this report the term inshore fisheries is used to describe shellfish fisheries (although there are elements of these fisheries, particularly for brown crab and scallop, which take place outside the 12 mile limit in what would be considered offshore areas). The terms “industry derived” and “fisher led” are used to describe data collection programmes which rely upon fishers collecting data within an appropriately designed data collection framework. The systems for collecting such data are the subject of further Work Packages within the SIFIDs project, which have yet to report.

1.1 Approach

In order to meet this aim, this report presents a combination of review material and a range of suggestions covering data types, data collection approach and data sampling designs, and stock assessment approaches. A substantial amount of the material that is covered is very technical and this part of the submission is, insofar as is practical, included in appendices. The high level structure of this document comprises a description of the Scottish inshore fisheries for lobster, crab, and scallops; a review section dealing with data collection; stock assessments and fisheries management; and a section which considers alternative approaches, again with respect to data collection, stock assessments, and fisheries management.

Industry led data collection will need to be tailored to reflect the fleet characteristics within each management unit, both from a practical point of view with regards to technological data collection methods and in order to ensure representative data collection. This report details the fisheries for each of the listed species; where they are carried out and by what type of vessels.

When considering the potential for fisher led data collection it is also important to gain an understanding of the existing data and the manner in which it is collected. This will aid in understanding what potential improvements in data collection can be made and what impact they might have on the overall quality of the data. Information is included on the current data collection programme including its spatial distribution, ownership, and its use in stock assessments.

There is also a need to examine the stock assessment models and outputs to determine if there are any biases which could impact on the effectiveness of management decision making. In examining the existing data and assessment techniques various approaches have been taken and these are fully detailed in Technical Appendix 1 to Technical Appendix 5.

The outputs of these review sections feed into observations on alternative data collection mechanisms and stock assessment approaches; and how optimised data collection utilising industry data might be implemented.

1.2 Description of the fishery

The data presented in this section is provided in order to give context to the fleet operating in different areas of Scotland. Any programme which will rely on industry derived data will require adequate consideration of the fleet structure within the geographical area of data collection. This is important in the identification of practicably suitable vessels to undertake sampling (e.g. vessels of sufficient size to house electronic equipment) and for data collection reasons (e.g. able to provide a sufficient sample size for the species in question).

Scottish inshore fisheries are predominantly based on shellfish with 75% of vessels from the inshore fleet originating from the creel sector¹. The most important shellfish stocks are the Norway lobster (*Nephrops norvegicus*), scallops (*P. maximus*), lobster (*H. gammarus*), and brown crab (*C. pagurus*). Although *Nephrops* is the second most valuable species landed into Scotland, it is subject to quotas and is not included within the scope of this report.

In 2015 a total of 43 644 tonnes of shellfish was landed in Scotland by Scottish vessels (Table 1.1), this having a total value of £113 562 000. Landings of *Nephrops* contributed over 50% of the total value landed, however, scallops and brown crab also make significant contributions to the landings.

Table 1.1 Landings and values of selected shellfish species in 2015, taken from “Scottish Sea Fisheries Statistics 2015” (Scottish Government, 2016).

Species	Landings (tonnes)	Value
Brown crabs	9 655	£12 124 000
Lobsters	1 208	£10 974 000
Scallops	10 108	£21 536 000
Total (including <i>Nephrops</i>)	45 644	£113 562 000

Some inshore vessels may switch to target finfish fisheries on a seasonal basis, although this will be dependent on the availability of quota and appropriate licence permissions. Some of the smaller creel vessels may target mackerel using jigging equipment while some of the larger vessels may fish for whitefish or squid as an alternative to scallops.

While the importance of pelagic and whitefish fisheries varies around the coast Figure 1.1 illustrates that shellfish fishing is important in all fishing areas around Scotland.

Both the brown crab and scallop fisheries consist of an inshore and offshore component. Areas such as Orkney, Sule, and Papa, tend to be prosecuted by larger brown crab vessels, including vivier crabbers, which can account for over 50% of the landings in some cases (Mesquita, et al., 2016).

¹ Figure obtained in May 2017 from www.gov.scot/Topics/marine/Sea-Fisheries/InshoreFisheries/ifmac

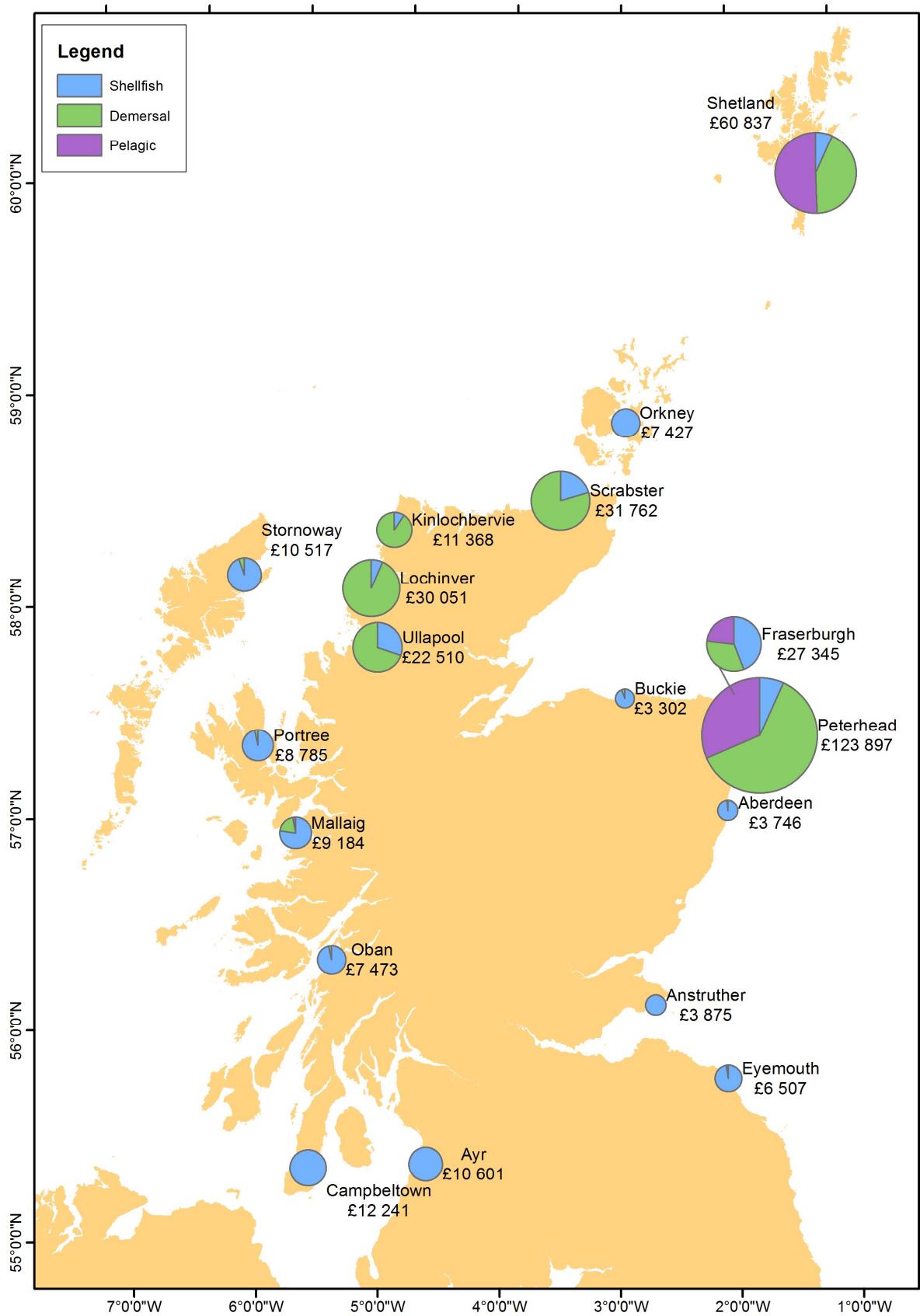


Figure 1.1 Value of landings into Scotland by all vessels by district (2015, £ thousands), values taken from “Scottish Sea Fisheries Statistics 2015” (Scottish Government, 2016).

1.2.1 Fleet structure

The Scottish fleet predominantly consists of vessels less than 10 m in length with 72% (1 449 vessels) of the fleet in this size category during 2015 (Scottish Government, 2016). The majority of these vessels are inshore vessels targeting shellfish, 88% of which are fishing with creels. Of those vessels over 10 m (566 vessels) 64% are shellfish vessels, although this figure includes those vessels targeting *Nephrops*. The under 10 m fleet is the largest fleet sector by area in all Scottish districts with the exception of Lochinver (Figure 1.2).

Updated figures for 2017 showed 1 474 vessels with a shellfish or scallop entitlement (Table 1.2). Of these, 87% (1 283 vessels) were creel fishers, 5.6% (83 vessels) were dredgers, and the remainder were trawlers (including *Nephrops* trawls) and “others” (e.g. hand lining; see Figure 1.3). Stornoway had the highest proportion of creel fishers (13.1%, 168 vessels) followed by Orkney (8.3%, 106 vessels) and Shetland (7.6%, 97 vessels). Ayr had the highest proportion of dredgers at 36.1% (30 vessels) followed by Shetland (15.7%, 13 vessels), and Campbeltown and Oban (10.8%, 9 vessels each).

Table 1.2 Number of vessels, their size, and gear type in the Scottish fleet during 2017 with a shellfish or scallop entitlement.

Gear type	Vessel size	Number	Proportion (%)
All	<10 m	1241	84.19
All	10 to 12 m	113	7.67
All	>12 to 15 m	38	2.58
All	>15 to 20 m	51	3.46
All	>20 m	31	2.1
	Total	1474	
Creels	<10 m	1176	91.66
Creels	10 to 12 m	87	6.78
Creels	>12 to 15 m	9	0.7
Creels	>15 to 20 m	9	0.7
Creels	>20 m	2	0.16
	Total	1283	87.04*
Dredge	<10 m	5	6.02
Dredge	10 to 12 m	7	8.43
Dredge	>12 to 15 m	18	21.69
Dredge	>15 to 20 m	28	33.73
Dredge	>20 m	25	30.12
	Total	83	5.63*

Stornoway and Shetland had the highest proportion (20%) of smaller vessels under 10 m in length (156 and 101 vessels, respectively) while Ayr had nearly 68% (21 vessels) of the over 20 m portion of the Scottish fleet with shellfish or scallop entitlement (Figure 1.4). This was reflected in the size breakdown of vessels by gear type of creels and dredges (Figure 1.5a and b, respectively). Nearly 92% (1 176 vessels) of creel vessels were under 10 m in length (Table 1.2) with the highest proportion based in Stornoway (13%, 154 vessels) followed by Shetland (8%, 95 vessels) and Fraserburgh (7%, 86 vessels). Orkney had the largest proportion (26 vessels) of larger vessels in the length size category of 10 to 20 m (Figure 1.5a). Overall, dredgers were found to be larger with nearly 64% (53 vessels) having an overall length greater than 15 m (Table 1.2). Ayr had the highest proportion of these (27 vessels), 18 of which were over 20 m in length (equating to 72 % within the size class). In contrast, nearly 62% (8 vessels) of the Shetland fleet were under 12 m in length.

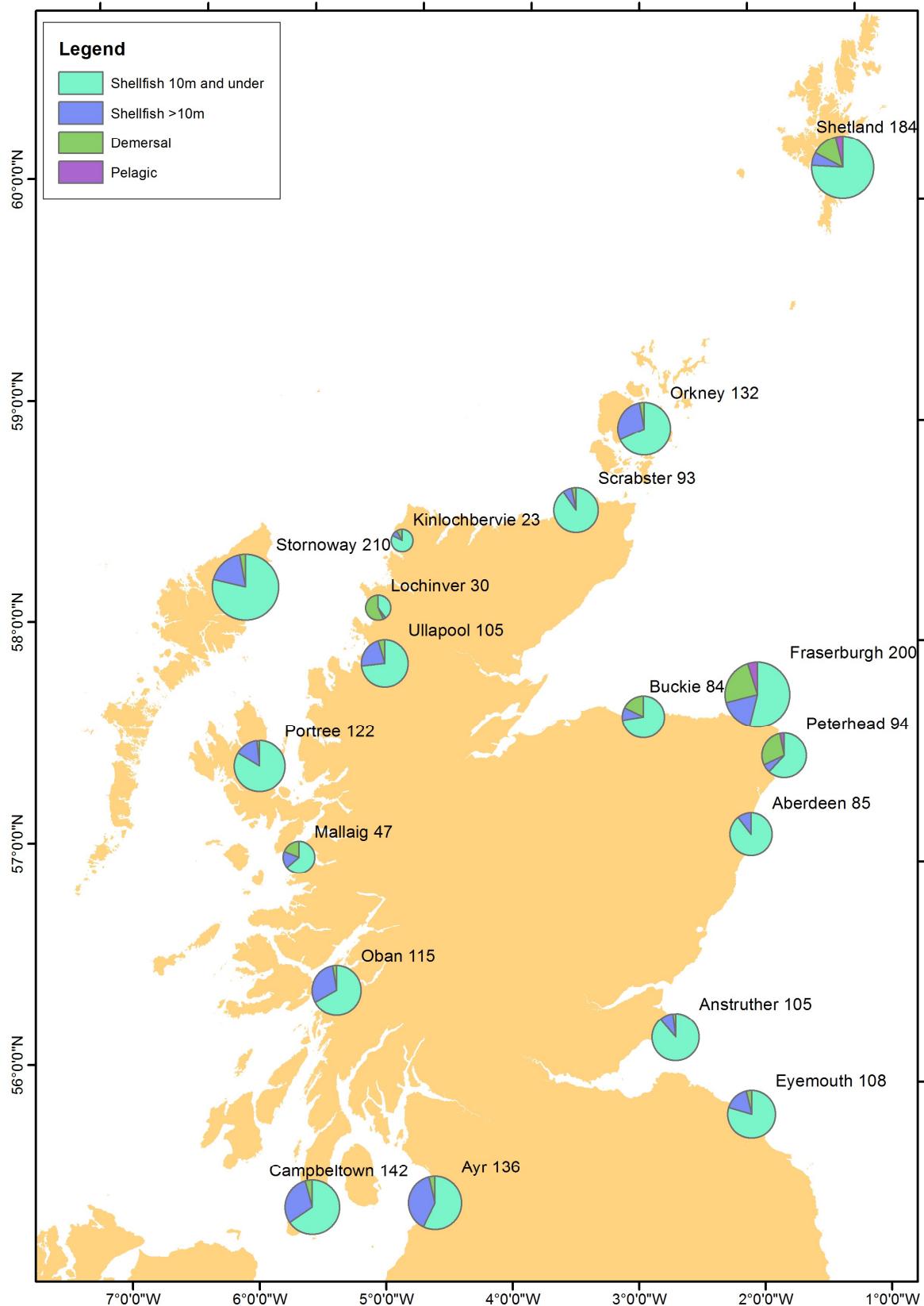


Figure 1.2 Number of vessels of each type in the Scottish Fleet by district during 2015, values taken from “Scottish Sea Fisheries Statistics 2015” (Scottish Government, 2016).

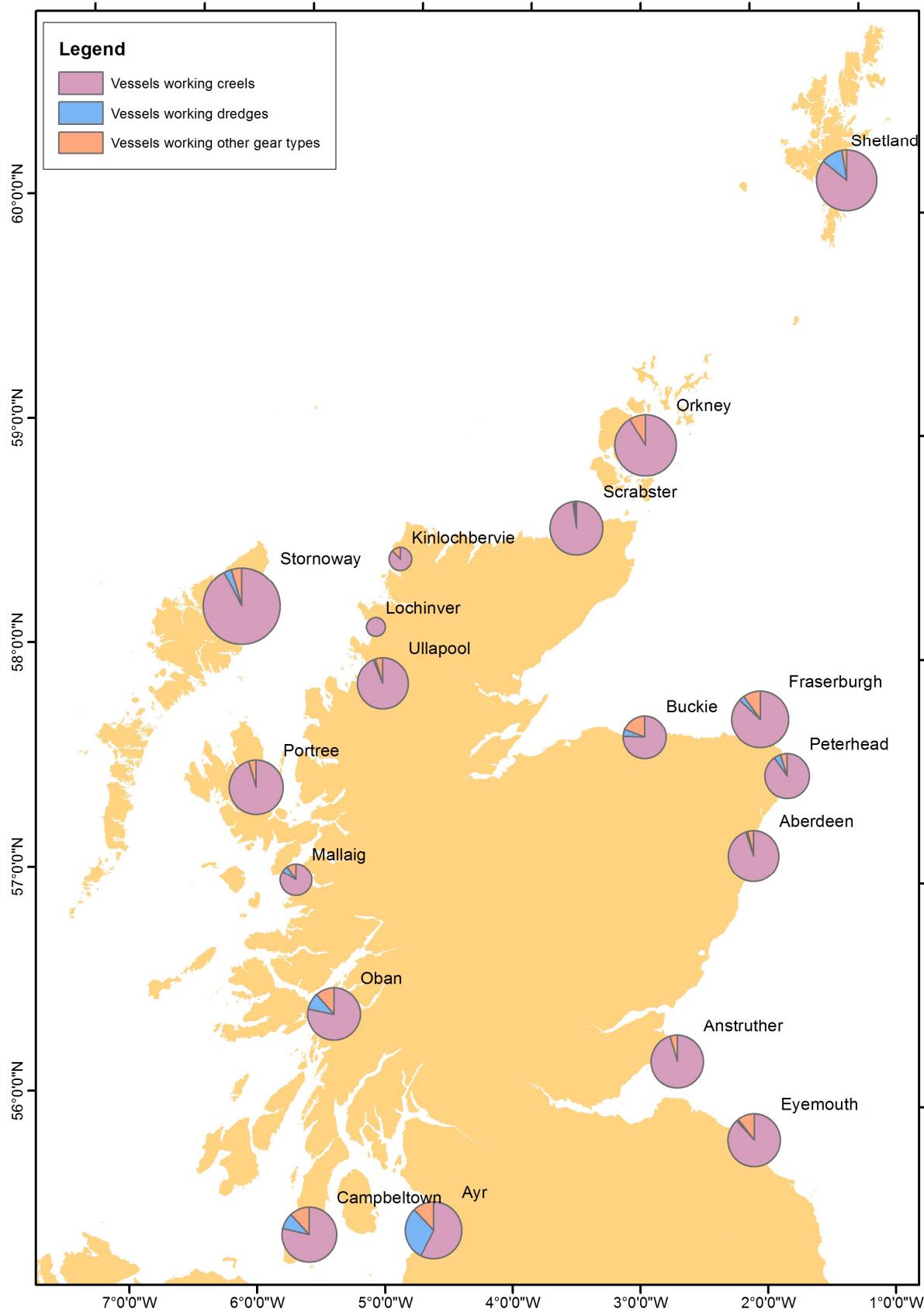


Figure 1.3 Number of vessels in the Scottish fleet with a shellfish or scallop entitlement during 2017, broken down by main gear types.

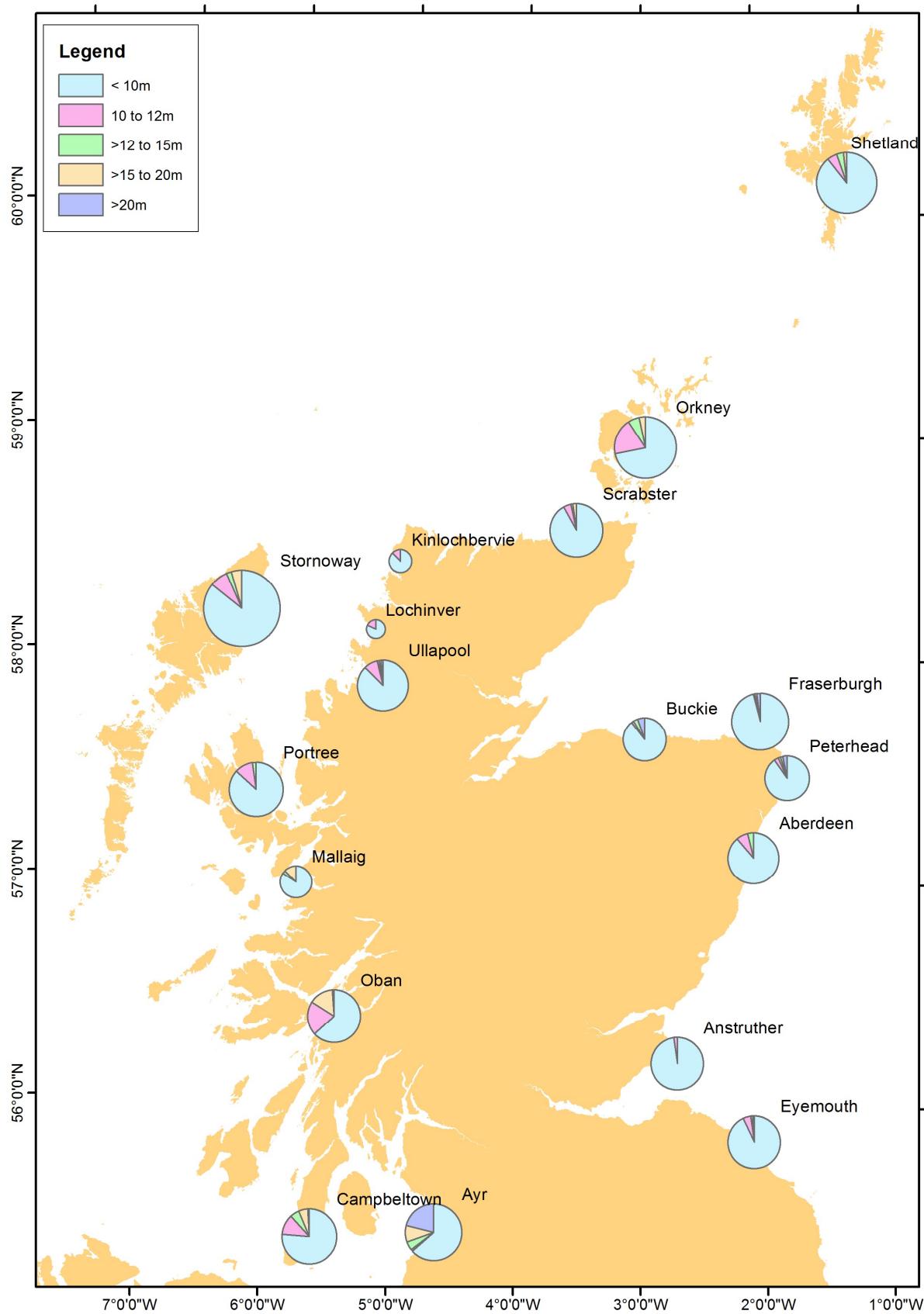


Figure 1.4 Number of vessels within each length category for all Scottish vessels with shellfish and scallop entitlement during 2017.

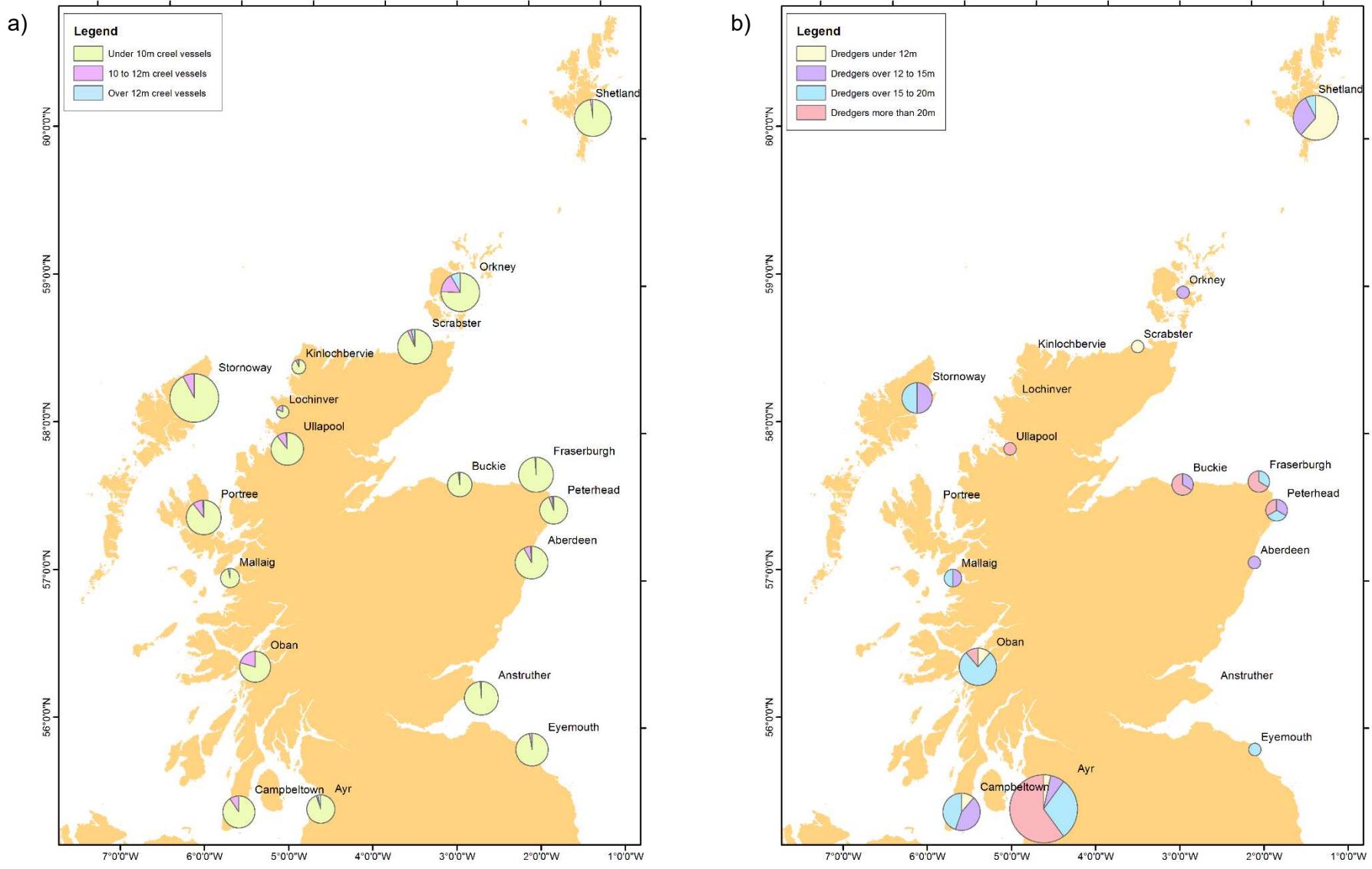


Figure 1.5 Breakdown of vessel size by gear type of (a) creels and (b) dredgers for the Scottish fleet during 2017.

The mean build year of the Scottish shellfish and scallop fleet was 1990 and when broken down by district had a mean range from 1985 (Eyemouth, Mallaig, and Orkney) to 1997 (Fraserburgh and Ullapool; see Figure 1.6). Orkney had the largest age range of vessels from 1905 to 2016 had some relatively newer builds, compared with other districts (Table 1.2). Orkney also had the highest number of builds pre 1980s with 36 vessels, Stornoway had 35 vessels for the same time period. Fraserburgh, Aberdeen, and Ayr had the greatest number of newest builds and no vessels older than the 1960s. Only two districts, Lochinver and Campbeltown, did not have any new builds during the 2010s. The newest build in Lochinver was in 2002, and 2007 in Campbeltown.

Table 1.3 Number of vessels in the Scottish fleet during 2017 built within each decade for each district and regional Inshore Management Group. Data was ordered by districts with the newest builds (at the top) through to those with older builds.

Regional Inshore Fisheries Group (RIFG)	District	pre 1950s	1950s	1960s	1970s	1980s	1990s	2000s	2010s
North and East Coast	Fraserburgh	0	0	1	4	18	18	19	18
North and East Coast	Aberdeen	0	0	1	9	14	15	20	15
West Coast	Ayr	0	0	9	14	16	15	20	3
Outer Hebrides	Stornoway	1	0	3	31	44	24	18	6
Orkney Management Group	Orkney	6	5	7	18	36	14	14	5
West Coast	Oban	0	0	4	19	21	13	14	3
SSMO	Shetland	1	1	5	11	21	23	8	4
West Coast	Portree	2	2	0	14	19	22	18	6
West Coast	Mallaig	2	1	2	5	2	8	4	1
North and East Coast	Scrabster	2	0	2	13	20	15	11	8
North and East Coast	Eyemouth	1	1	3	12	19	11	5	2
West Coast	Campbeltown	1	1	2	14	29	12	11	0
North and East Coast	Anstruther	1	0	1	6	27	16	9	3
North and East Coast	Buckie	0	0	3	6	8	12	7	6
North and East Coast	Peterhead	0	0	1	4	17	10	8	7
West Coast	Ullapool	0	0	1	4	10	8	14	11
West Coast	Lochinver	0	0	0	3	2	3	2	0
West Coast	Kinlochbervie	0	0	0	2	3	2	1	1

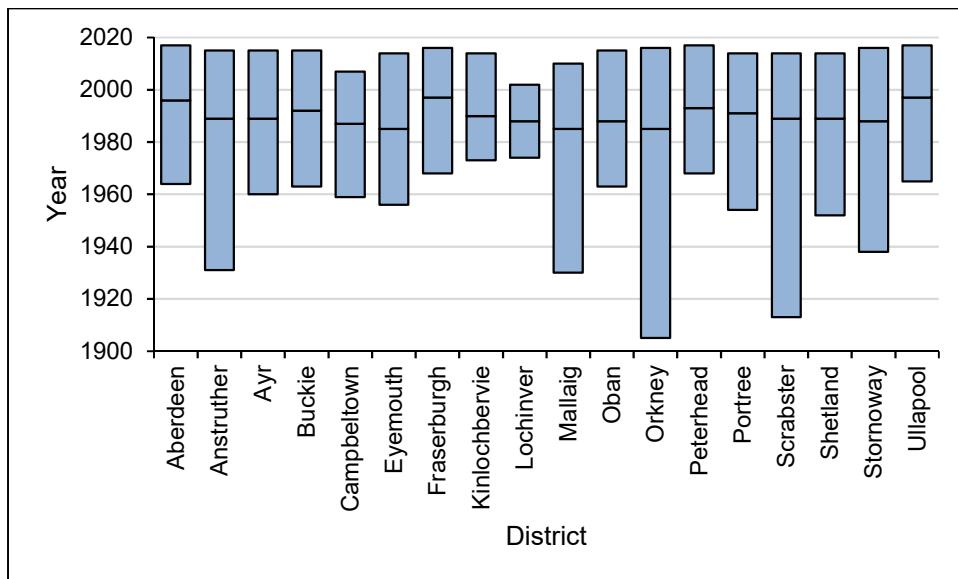


Figure 1.6 Age range of vessels with a shellfish or scallop entitlement in the Scottish fishing fleet by district during 2017. Mean build year denoted by solid line within each age range.

Shellfish are landed throughout Scotland (Figure 1.1 and Figure 1.7) with Ayr, Campbeltown, and Orkney being three of the main landing districts where shellfish are a high proportion of overall landings. In contrast, Shetland, Peterhead, Fraserburgh, and Scrabster did not have a high proportion of shellfish landings, compared to their demersal and pelagic landings, but did have relatively high overall shellfish landings when compared to other ports (Figure 1.7).

Districts in northwest Scotland had the highest proportion of brown crab landings in 2015 with five of these seven districts had more than 75% of landings, from the three study species, attributed to brown crabs (Figure 1.8a). Of the three study species, only brown crabs were landed in Lochinver and no brown crabs were landed in Ayr.

The highest proportion of lobster landings were recorded from districts along the east coast (Aberdeen, Anstruther, and Eyemouth), Stornoway, and Orkney (Figure 1.8b). Six of the 18 districts had no lobster landings in 2015.

Scallop landings high in Shetland, Fraserburgh, Peterhead, Oban, Campbeltown, and Ayr all of which had scallop landings greater than 60% of the total landings for the three species (Figure 1.8c). Landings from Mallaig and Buckie were also dominated by scallops although not in as high quantities as those from the six main districts listed above.

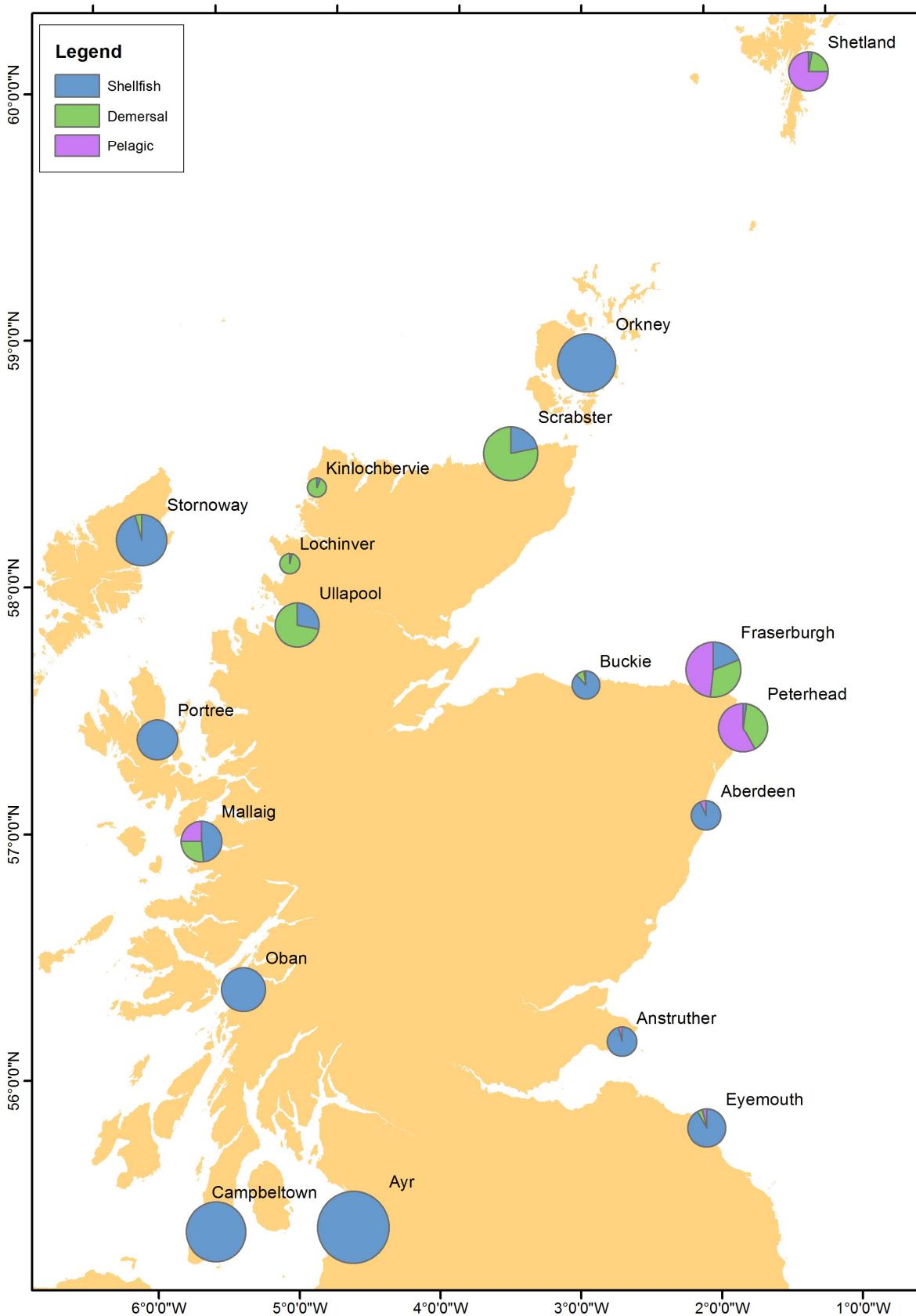


Figure 1.7 Landings (tonnes) of shellfish (blue), demersal (green), and pelagic (purple) species for each district in 2015, values taken from “Scottish Sea Fisheries Statistics 2015” (Scottish Government, 2016). Pie chart size relates to proportion of total shellfish landed from all districts.

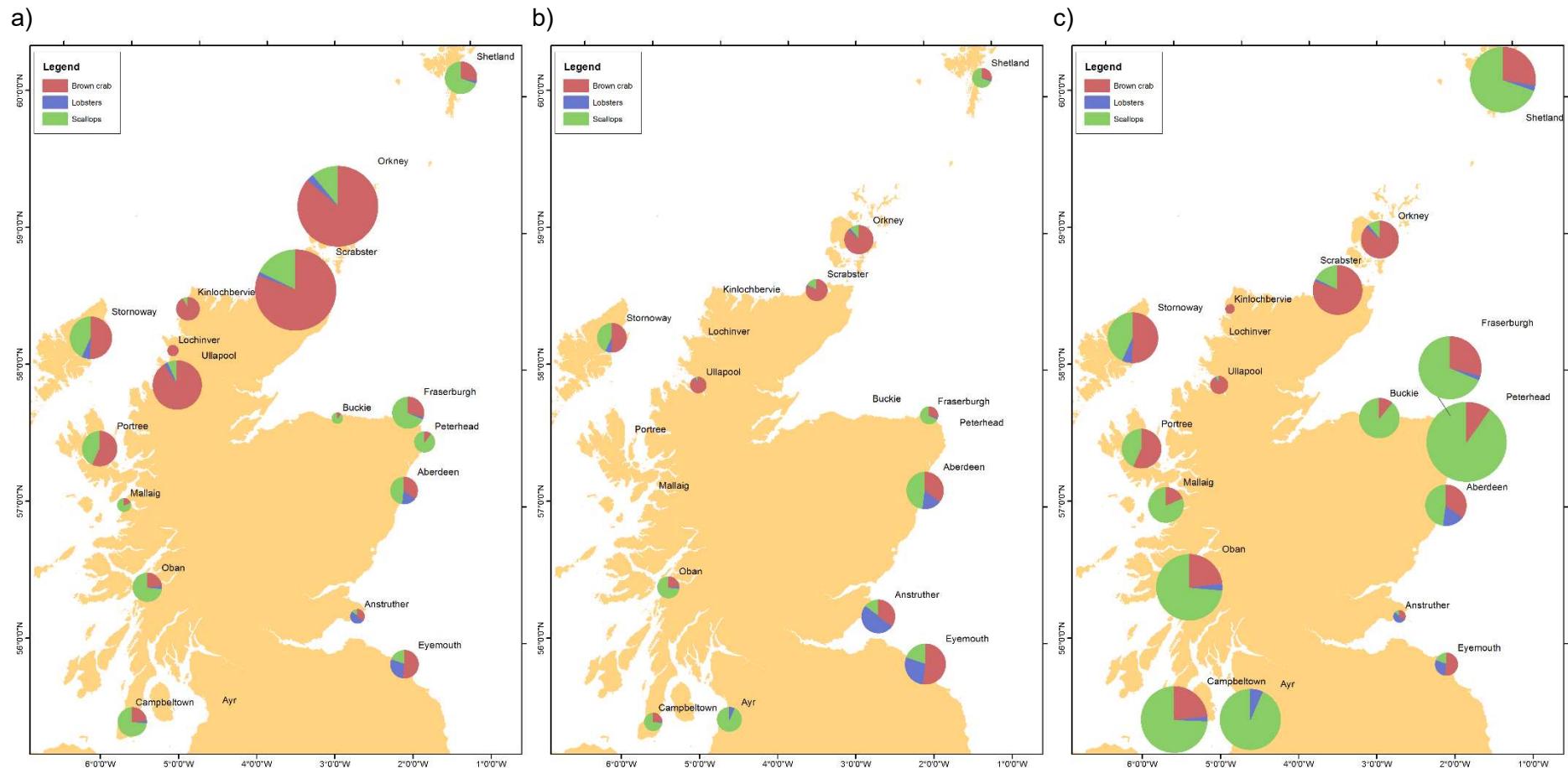


Figure 1.8 Landings (tonnes) of brown crab (red), lobster (blue), and scallop (green) for each district in 2015, values taken from “Scottish Sea Fisheries Statistics 2015” (Scottish Government, 2016). Pie chart sizes determined by the proportion of the total landings for each district based on brown crab landings (a), lobster landings (b), and scallop landings (c).

1.3 National management

Inshore fisheries management is implemented at the national level by Marine Scotland. Fishing vessels wishing to target shellfish must have a shellfish licence with the appropriate entitlements for species attached. The Scottish Government currently operates a restrictive licensing system with no new licences or entitlements being issued. There are however latent licences within the system and therefore the potential for increased effort should these become active.

A recent report published by the Marine Analytical Unit of Marine Scotland Science looked at creel fishing effort from four regions around Scotland (Marine Scotland Science, 2017). The findings concluded that there was a clear need to review the current shellfish management system and highlighted that management of creel fishing (for crabs and lobsters) should be “tackled at the local level”. At the national level, there is limited effort management for crabs and lobsters which have been summarised by Marine Scotland Science (2017). The authors noted that there are no EU effort restrictions on these creel fisheries for vessels under 15 m in length with a minimum landing size (MLS) being the main management measure across Scotland.

Legislation for Scottish inshore fisheries management is covered by three main acts: the Inshore Fishing (Scotland) Act 1984²; Sea Fish (Conservation) Act 1967³; and Sea Fisheries (Shellfish) Act 1967⁴. Marine Scotland Science (2017) summarises each of the Acts. Additional management measures have been implemented through a series of Orders and include such measures as v-notching lobsters, alterations to minimum landing sizes, defining areas of prohibited fishing, amongst others. The Inshore Fishing (Prohibition of Fishing and Fishing Methods) (Scotland) Order 2015 outlines prohibited fishing methods from 13 protected areas around Scotland with more recent Orders in place for Luce Bay⁵ and the Outer Hebrides⁶, in addition to similar Orders pre 2015. The Sea Fisheries (Shellfish) Act 1967 permits the granting of Several Orders and Regulating Orders which are made for establishment and improvement, and for maintenance and regulation, of a shellfish fishery. The Shetland Islands Regulated Fishery (Scotland) Order 2012⁷ grants fisheries management responsibilities for shellfish fisheries within six nautical miles of the Shetland Islands to the Shetland Shellfish Management Organisation (SSMO).

The Undersized Lobsters (Scotland) Order 2000 stipulates a MLS for lobsters of 87 mm with subsequent orders for Orkney and Outer Hebrides increasing their MLS to 90 mm. In addition, the Outer Hebrides have a maximum landing size for female lobsters of 145 mm and have prohibited the landing of crippled (those missing a claw) female lobsters. Under The Lobsters and Crawfish (Prohibition of Fishing and Landing) (Scotland) Order 1999, it is illegal to fish for or land any v-notched lobster within the Scottish Zone.

² www.legislation.gov.uk/ukpga/1984/26/contents

³ www.legislation.gov.uk/ukpga/1967/84/contents

⁴ www.legislation.gov.uk/ukpga/1967/83

⁵ www.legislation.gov.uk/ssi/2015/436/contents/made

⁶ www.legislation.gov.uk/ssi/2017/48/contents/made

⁷ www.legislation.gov.uk/ssi/2012/348/pdfs/ssi_20120348_en.pdf

Minimum Landing Sizes of brown crabs are outlined by The Undersized Edible Crabs (Scotland) Order 2000 which lists the MLS to be either 130 or 140 mm, depending on area, for both males and females. The Outer Hebrides have increased the MLS of male and female brown crabs to 150 mm. No Orders have been issued restricting effort for either brown crab or lobster.

New scallop conservation measures (The Regulation of Scallop Fishing (Scotland) Order 2017) came into effect on 1st June 2017 covering all vessels dredging for king scallops within 12 nm in Scottish waters⁸. As part of these measures, the minimum landing size for king scallops increased from 100 mm to 105 mm (with the exception of the Irish Sea south of 55°N and Shetland), and dredge numbers have been restricted to no more than eight dredges per side. If vessels are fitted with a remote electronic monitoring system, they are permitted to tow up to eight dredges per side within the 0 to 6 nm area and up to ten dredges per side within the 6 to 12 nm area. The remote electronic monitoring system must include a control box capable of housing and storing software and data, a minimum of two digital cameras, winch sensors, a GPS which records the vessel's movements every 10 seconds, a way of viewing the information, and a way of extracting the information. Minimum specifications are detailed for each requirement on the Scottish Government webpage.

For unlicensed vessels, The Shellfish (Restrictions on Taking by Unlicensed Fishing Boats) (Scotland) Order 2017 defines the quantity of each species allowed to be taken in a day which includes one lobster, five crabs, and six scallops. The Order does not impose any effort limits for unlicensed vessels.

1.4 Regional management

Inshore fisheries management at the regional level has been facilitated following a Strategic Review of Inshore Fisheries which began in 2002 which resulted in the publication of 'A Strategic Framework for Inshore Fisheries in Scotland (2005)'. This was superseded by a further Inshore Fisheries Strategy in 2012 and following review in 2015.

Five Regional Inshore Fisheries Groups (RIFGs) have been established around Scotland and their remit extends out to the 6 nm limit (Figure 1.9). The RIFGs are non-statutory bodies with the aim of improving inshore fisheries management around Scotland and providing the commercial fishers with a strong voice in wider marine management developments. Information obtained through RIFGs could then be incorporated into and considered by the eleven Scottish Marine Regions (Figure 1.9). Scottish Marine Regions extend out to the 12 nm limit with each region developing a Marine Planning Partnership. The Clyde and Shetland Isles are the first regions to take forward regional marine planning.

⁸ For more details: www.gov.scot/Topics/marine/Sea-Fisheries/InshoreFisheries/scallopconservation

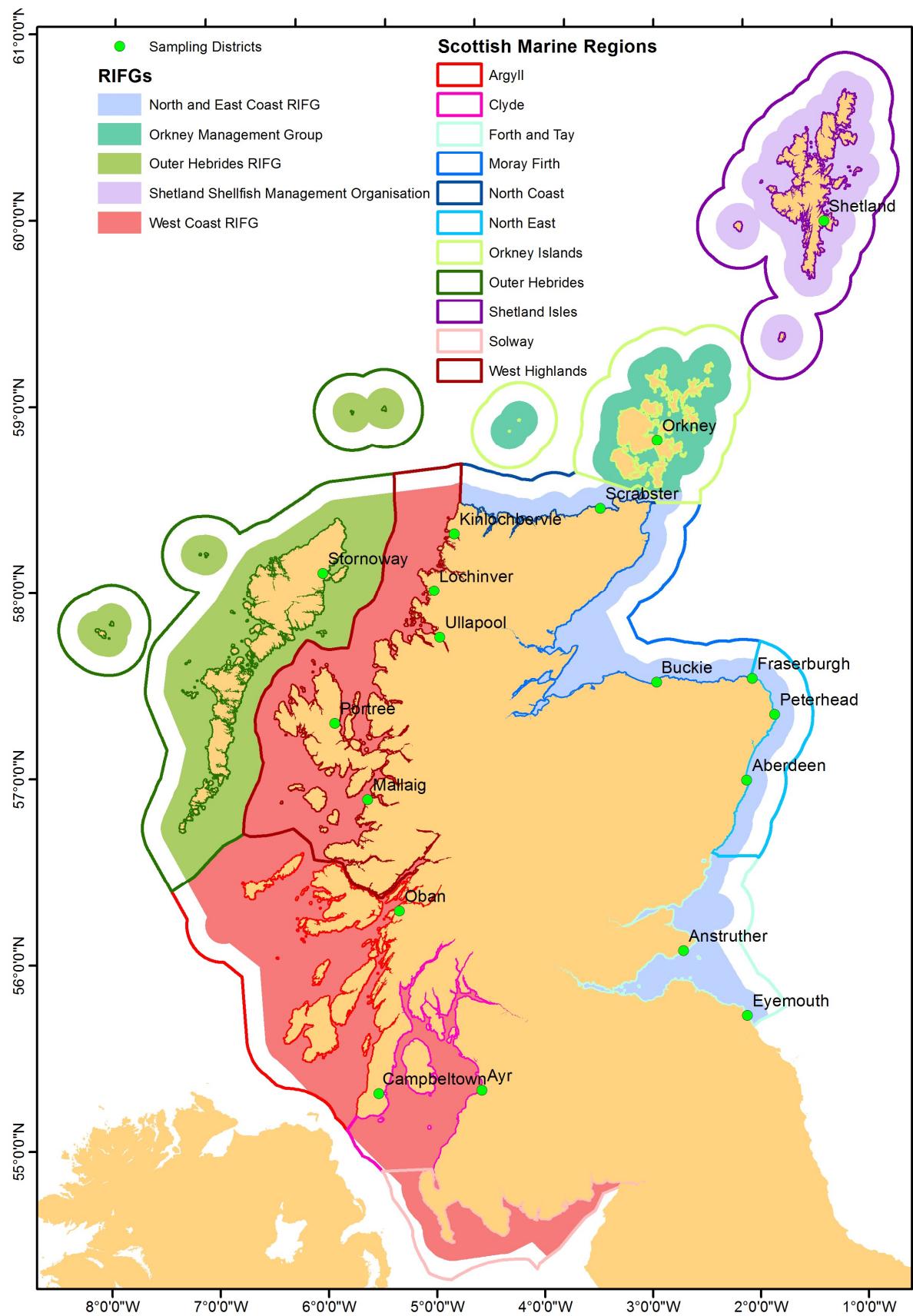


Figure 1.9 Map showing the boundary areas of the Regional Inshore Fisheries Groups (RIFGs) and the sampling districts. Scottish Marine Regions, extending out to the 12 nm limit, are overlaid as outlines.

The Inshore Fisheries Strategy underpinning the RIFGs includes a focus on: improving the evidence base on which inshore fisheries management decisions are made; streamlining fisheries governance, promoting stakeholder engagement; and on embedding inshore fisheries management into wider marine planning. Some of the key strategy outcomes, directly relevant to this work package are:

Outcome 2: To implement appropriate vessel monitoring by 2020.

Outcome 4: Manage inshore waters in a way which is environmentally sustainable, by having effective assessment methodologies in place for fishing at Maximum Sustainable Yield (MSY) and achieving Good Environmental Status (GES) in a way which is congruent with the Marine Strategy Framework Directive (MSFD).

Outcome 5: Develop a baseline of data to better understand the fishing footprint and interactions between sustainable fishing and other activities in the marine environment.

Also stated within the Inshore Strategy is an emphasis on better data collection (landings and effort) to allow for enhanced management at a local level and for meeting the MSFD obligations.

Each of the RIFGs have differing fisheries management aspirations, but all areas have indicated through the development of their management plans that improved data are required to facilitate their aims.

East coast RIFG (now part of the North and East Coast RIFG) “*there is a need to create an evidence base upon which to establish rational management measures.*”

Moray Firth and North Coast RIFG (now part of the North and East Coast RIFG) “*The FMP is based on the premise that rational management measures will be founded on clear evidence and that the aim of various aspects of the plan is to generate such information. In virtually all situations the sourcing of data will have a direct financial cost which will need to be met if management measures are to be progressed.*”

North West RIFG (now part of the West Coast RIFG) “*The data is gathered by ICES rectangles which are approximately 30 nautical miles square. Whilst such data is useful for government in terms of quota management decisions, it is not detailed or rigorous enough to inform local fisheries management especially as no fishing effort data is routinely collected.*”

South West RIFG (now part of the West Coast RIFG) “*Objective 2: Improve the quality of the fisheries data available to inform IFG level management.*”

Orkney Management Group, led by Orkney Sustainable Fisheries, has been carrying out a wide range of locally lead data collection including observer data collection at sea. Their management plan states “*...management measures may be developed in the future, where local science and stock assessment demonstrates that they have a value to the future of the fishery...*”

As previously outlined, regional management in Shetland has been devolved to the Shetland Shellfish Management Organisation (SSMO) via a Regulating Order. All vessels fishing within the 6 nm limit are required to have a Shetland Shellfish Licence and must abide by the local regulations. This includes the submission of logbook data detailing catch, effort, fishing location, discards (and reason for return), target species, and any interactions with Endangered Threatened or Protected (ETP) species or habitats. These data are managed, analysed, and reported by the NAFC Marine Centre via a fisheries management database, and is integrated into an active management plan, using Harvest Control Rules facilitated by a series of fisheries reference points. The Regulating Order has been in place since 2000 and therefore means that shellfish fisheries in Shetland are relatively data rich and provides an example of an integrated data collection and management system which supports fisheries management and informs marine spatial planning via the Shetland Islands' Marine Spatial Plan and Shetland Planning Partnership.

2 REVIEW OF CURRENT DATA COLLECTION AND STOCK ASSESSMENT

2.1 Data collection methodologies

Data collection, reporting, and stock assessment in Scotland is carried out by Marine Scotland Science⁹. The main aims of this data collection are to meet EU reporting obligations, to determine the value of the sector, and to provide a determination of the status of the stocks. Data are obtained via returns from the fishing industry and through sampling programmes carried out by Marine Scotland.

For the purposes of representing the data collection processes the data have been split into two broad categories; fisheries data (e.g. landings, effort, location) and biological data (e.g. size, age, sex). The protocols for data collection, management, storage, and further use are detailed in the following sections.

2.1.1 *Fisheries data collection and management*

Fisheries data is that which is directly attributed to the activity of the vessel, and includes when and where fishing occurs and the catch taken and landed for each fishing trip. There is a requirement for reporting of fishing activity under EU legislation which has been transcribed into Scottish Law via the Sea Fishing (EU Recording and Reporting Requirements)(Scotland) Order (SSI 2010/334). For the inshore fleet fishing data are recorded in a number of different ways as detailed in Table 2.1. Fisheries data provided on logsheets has historically been entered into the Fisheries Information Network (FIN) administrative database, however this was to be replaced by a new system, COMPASS, in 2017.

Table 2.1 Reporting requirements for different size classes of inshore fisheries vessels.

Vessel size	Reporting format	Spatial data	Frequency
<10 m	FISH1 Form	ICES stat square and lat long on start of fishing	Weekly
10-12 m	Paper EU logsheet	ICES stat square and lat long on start of fishing	Daily
>12 m	E-log	ICES stat square and mandatory VMS	Daily

Data entered on FISH1 Forms (Figure 2.1) must be submitted weekly; the form provides the option for fishers to include data on a daily basis with a separate line for each day, however, despite it being mandatory for daily recording some fishers will just provide an aggregated catch for the week. Some sheets are submitted electronically (by email), others are filled in by hand and currently all must be entered into the system by Marine Scotland Compliance (MSComp) staff. Logsheets are typically submitted to the local fisheries office in a fairly regular and timely manner. Marine Scotland Compliance also receive data from shellfish buyers who are required to provide sales notes giving details of fish bought at first sale. The sales notes completed by buyers and sellers must be submitted within 48 hours and therefore

⁹ It should be noted that Marine Scotland Science is only responsible for biological sampling data and surveys. Official fishery data (from logsheets and VMS) are a responsibility of Marine Scotland Compliance

it is possible to determine when a vessel is fishing but has perhaps not submitted logsheets, and they can therefore be contacted to remedy this

Figure 2.1 Fish 1 form.

The new database system (COMPASS) has been developed to allow direct entry of the data into the system via a mobile phone app, though this method of data gathering is not currently available to fishers. The FISH1 Form allows for the reporting of positional data, including the start point of the days fishing activity and the ICES statistical rectangles. If the vessel has fished in more than one statistical square, only the start point or the first square written will be entered into the database, as it cannot accept multiple fishing areas. Although currently data are being collected on the start location of fishing activity it is not being captured until the COMPASS database is fully up and running.

A mandatory, working Vessel Monitoring System (VMS) is fitted to all EU vessels 12 m or greater in length. In Scottish waters, these units report (ping) the vessel's details, including information on the vessel's position and speed (used as an indicator of the vessel's activity), every two hours. The information is held by MSComp but ownership is retained by the vessel owner/skipper. In 2017, a total of 18 creel vessels (1.4% of creel fleet) and 71 scallop dredgers (85.5% of dredge fleet) would have had VMS units fitted (Figure 1.5). However, the reporting frequency of the units were intended to capture activity from the demersal and pelagic trawl fisheries and not inshore fisheries where the duration of fishing activity (e.g. tow length) can be much shorter compared with offshore. Recent work has shown that the current reporting frequency of two hour pings is not a good representation of all fishing types, including some whitefish fishing (Katara and Silva, 2017) and this can lead to misrepresentation of actual fishing activity (Shelmerdine, *et al.*, 2017). In the case of scallop dredging, a 10 minute reporting frequency has been shown to provide excellent information on fishing activity and behaviour when using an inshore VMS (iVMS) system (Shelmerdine and Leslie, 2015), with some regions increasing the frequency further to a one minute ping interval (MMO, 2012) in order to monitor compliance of vessels fishing outside a closed area boundary. In Scotland, only Shetland operates an iVMS system fitted aboard inshore scallop vessels. These units report every ten minutes to a secure database where vessel activity can be monitored in real time or analysed historically (Shelmerdine and Leslie, 2015).

While there has been space on logsheets to record effort data prior to the introduction of the FISH 1 form and COMPASS database, this data was not entered or processed within the FIN database due to limited resourcing. Consistent effort data linked to fishing activity is therefore only available for period since the FISH 1 form came into active use. This has begun a time series of data, however, this data was not available for analysis as part of this study due to a backlog in the data entry for inshore fisheries. It is expected that effort data from July 2016 onwards will be available via COMPASS in 2018. Effort data was collected as part of a study carried out by Marine Scotland Analytical Unit in 2017, however data was shared by fishers using a confidentiality agreement, meaning that all participants would have to be contacted to release the data for any other purpose. The only area for which there is a time series of reliable effort data for both creels and dredges is in Shetland, where this information is gathered as part of local fisheries management measures (as outlined in Section 1.4).

There is no specific quality control process for the checking of data following entry at the local level, although the weight of landings recorded on logsheets is verified against the sales data collected from the buyers. The value from the sales record is considered to be the landing declaration and is what is recorded in the database. The fishers are generally allowed around

a 10% variance on the information submitted on the logsheet when compared with the more accurately weighed sales record. As shellfish (other than *Nephrops*) are non-quota species, irregularities in reporting are not always followed up, as they are seen as a lower priority than quota species and this level of scrutiny of the data is not cost effective.

For data reporting purposes the administrative databases (e.g. FIN) are subject to additional quality assurance work by the Marine Scotland Data Team (Scottish Government, 2016), to ensure there is consistency between data sets, check for missing data, and allow for stakeholder input. The fisheries statistics report acknowledges that there are considerable delays to data entry for species which are not subject to quotas.

Data from the COMPASS database along with VMS data and sales information is stored in the “UK’s communications data hub” from which data are extracted at the UK level for reporting to the EU Commission. Within the Hub there are various levels of permission for access to the data, including fishers being able to access their own data. The fisher remains the owner of their information while the Hub provides a secure environment for their information. Although data requests can be made for information, no data can be released to a third party which has the potential to identify a fisher, a vessel, or individual fisher or vessel activity.

2.1.2 Biological data collection and management

Biological shellfish sampling is carried out by Marine Scotland Science (MSS) as part of the EU Data Collection Framework¹⁰, to provide representative samples from the fisheries assessment areas shown in Figure 2.2 and Figure 2.3. There are a total of 15 sampling strata plus Shetland with the frequency of visits varying from two to eight per year. The design of the scheme makes a broad distinction between these 15 sampling strata and Shetland, with sampling in Shetland carried out under a Memorandum of Understanding with the NAFC Marine Centre. The sampling strata are based on geographic regions and include landing ports and local processors. Marine Scotland Science estimate that the strata cover about 78% of the shellfish landed into Scotland. The frequency of sampling is affected by ease of access and cost with island areas, such as the Hebrides and Orkney, only being visited twice per year (sampling in Shetland is carried out more frequently than the other island groups through the MoU with NAFC Marine Centre). The type of fishery can also affect the availability of data, brown crabs and lobsters may be stored for a period of time after being landed, making them easier to access than velvet crabs which are often landed at remote harbours and shipped live to the continent which can make sampling more difficult (Mesquita, et al., 2016). Shellfish sampling is carried out by a single person and the length of time spent in each area varies from one to six days (Table 2.2). The data collection is shore based with no on-board observer programme in place, although some ad hoc trips may take place and sampling in Shetland includes some data recorded by observer sampling at sea.

¹⁰ <https://datacollection.jrc.ec.europa.eu/>

Table 2.2 Summary of sampling strata, duration, and frequency broken down by regional Inshore Fisheries Group (RIFG) areas.

Sampling strata	Regional Inshore Fisheries Group (RIFG)	Number of nights	Sampling frequency
Eyemouth	North and East Coast RIFG	2	Monthly/twice per ¼
Moray Firth	North and East Coast RIFG	2	Monthly/twice per ¼
NE Shellfish	North and East Coast RIFG	3	Monthly/twice per ¼
Pittenweem/ Johnshaven	North and East Coast RIFG	2	Monthly/twice per ¼
Scrabster	North and East Coast RIFG	2	Quarterly
Orkney	Orkney Management Group	5	Biannually
Stornoway	Outer Hebrides RIFG	5	Biannually
Uist	Outer Hebrides RIFG	5	Biannually
Lerwick/Scalloway	SSMO	N/A	
Ayr/Solway	West Coast RIFG	2	Quarterly
Campbeltown/ Tarbert	West Coast RIFG	2	Monthly/twice per ¼
Mallaig/Fort William	West Coast RIFG	2	Monthly/twice per ¼
Oban	West Coast RIFG	2	Monthly/twice per ¼
Skye	West Coast RIFG	2	Monthly/twice per ¼
Torridon	West Coast RIFG	1	Quarterly
Ullapool	West Coast RIFG	1	Quarterly

The shore-based sampling programme collects data on five separate species of shellfish; king scallops (*Pecten maximus*), brown crab (*Cancer pagurus*), and European lobster (*Homarus gammarus*) which are considered in this report but also includes Norway lobster (*Nephrops norvegicus*) and velvet crab (*Necora puber*). Biological data, providing information about the characteristics of the species caught (see Table 2.3), is stored on a central database by Marine Scotland Science (MSS) staff.

The entry of biological data for crab and lobster from the shore-based sampling programme is carried out twice a year, and for scallops it may be entered monthly or quarterly. The data are only accessible by MSS staff and used for stock assessment purposes. Any data requests would require a member of staff to access the data and process the raw information prior to it being shared. At the time of writing, the MSS database and the sampling procedures were undergoing change which had not been finalised.

Table 2.3 Summary of shore-based biological sampling.

	Brown crabs and lobsters	King scallops
Measured data	Carapace width (brown crab) Carapace length (lobster)	Shell width Age Meat yields*
Recorded data	Weight landed (no of boxes per category) Number sampled (boxes) Port landed Date Vessel	Total landings (number) Number sampled (numbers) Port landed Date Vessel
Sampling categories	Sex Berried Damaged	5 mm intervals (rounded down). ≥10 years, mark as 10 years.
Number sampled	Min 500 per ¼	1 bag (\approx 100) per vessel
Resolution	ICES square	ICES square

* In Shetland, one bag of scallops for each of the four ICES statistical rectangles per quarter is sampled for scallop meat yields.

There are proposed changes to the data collection methodologies at the national level following the production of an international report looking at probability-based selection methodologies on a regional sampling basis (MASTS, 2016).

For scallop data the most recent stock assessment document (Dobby, *et al.*, 2017) states that there has been a reduction in the collection of commercial sampling data for scallops due to limited staff availability and a prioritisation of other activities. This reduction in sampling data are highlighted as a potential threat to the quality of stock assessment outputs, should it continue.

In addition to data collected from commercial fishing trips there are also data included in the assessments from scallop surveys. The surveys have been in place since the mid-1990s and constitute three separate surveys covering the west coast, North Sea, and Shetland. The survey design includes fixed stations which have been derived with reference to sediment data from British Geological Survey charts, and fishers knowledge at the time of survey design (Dobby, *et al.*, 2012). The survey uses a standard array of Newhaven dredges and a further sampling array with a smaller configuration based on queen scallop dredges. More recent survey sampling has also been informed by VMS data from the scallop fleet (H. Dobby, pers. comm.).

A diagrammatic representation of how the data feeds in to each database and the further flow of data through to fisheries management illustrates how complex the system is (Figure 2.4).

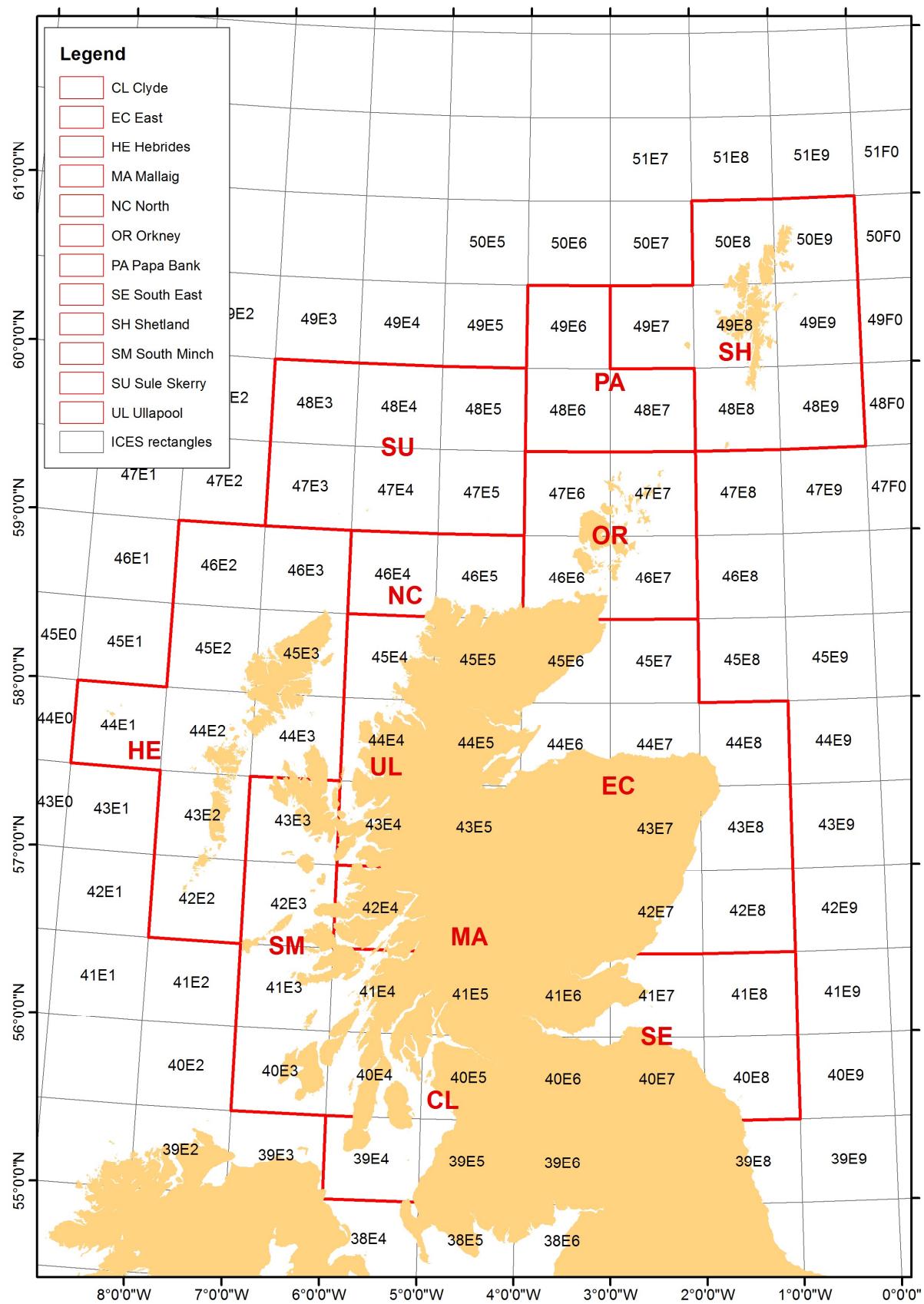


Figure 2.2 Shellfish Assessment Areas for crabs.

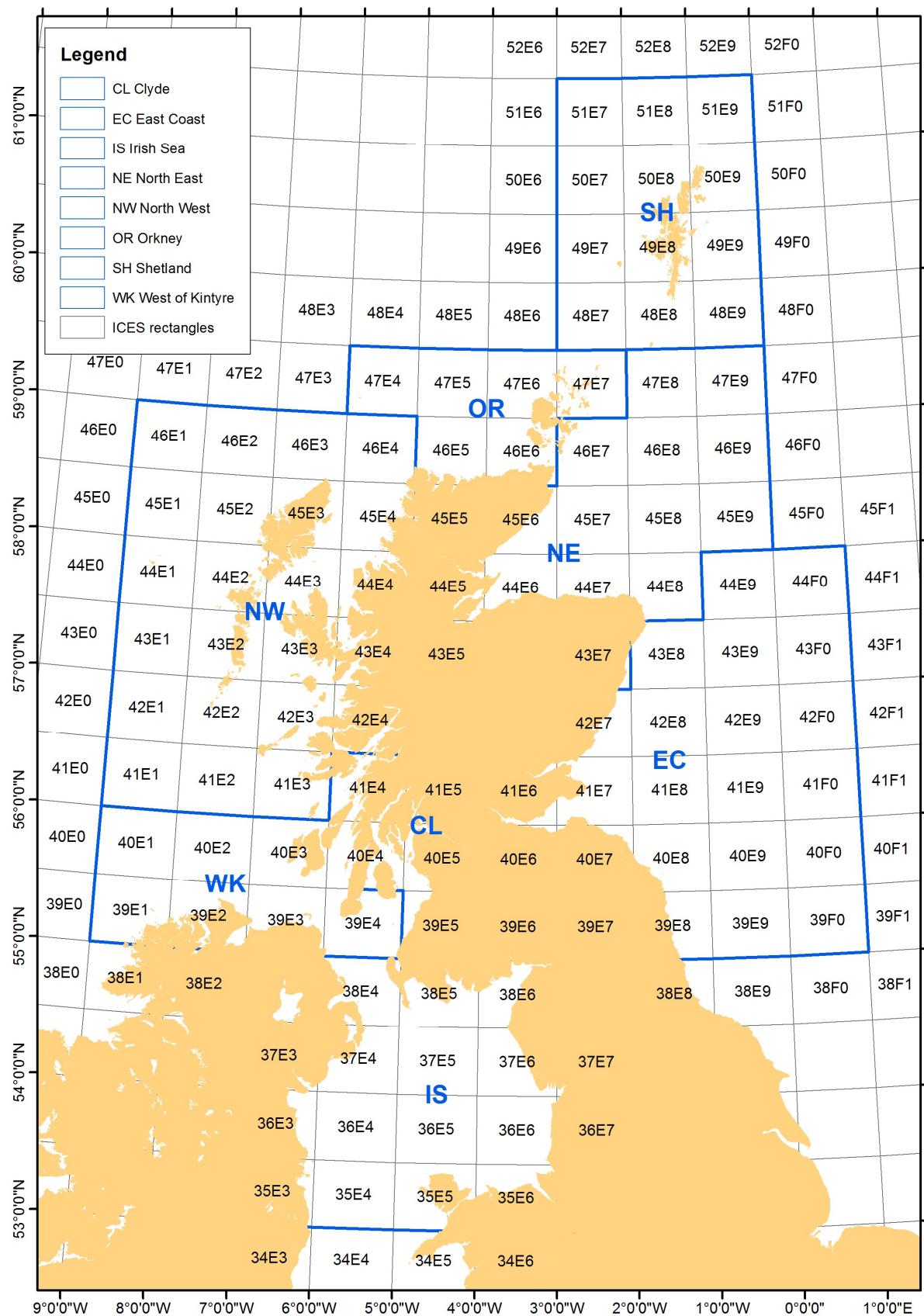


Figure 2.3 Shellfish Assessment Areas for scallops.

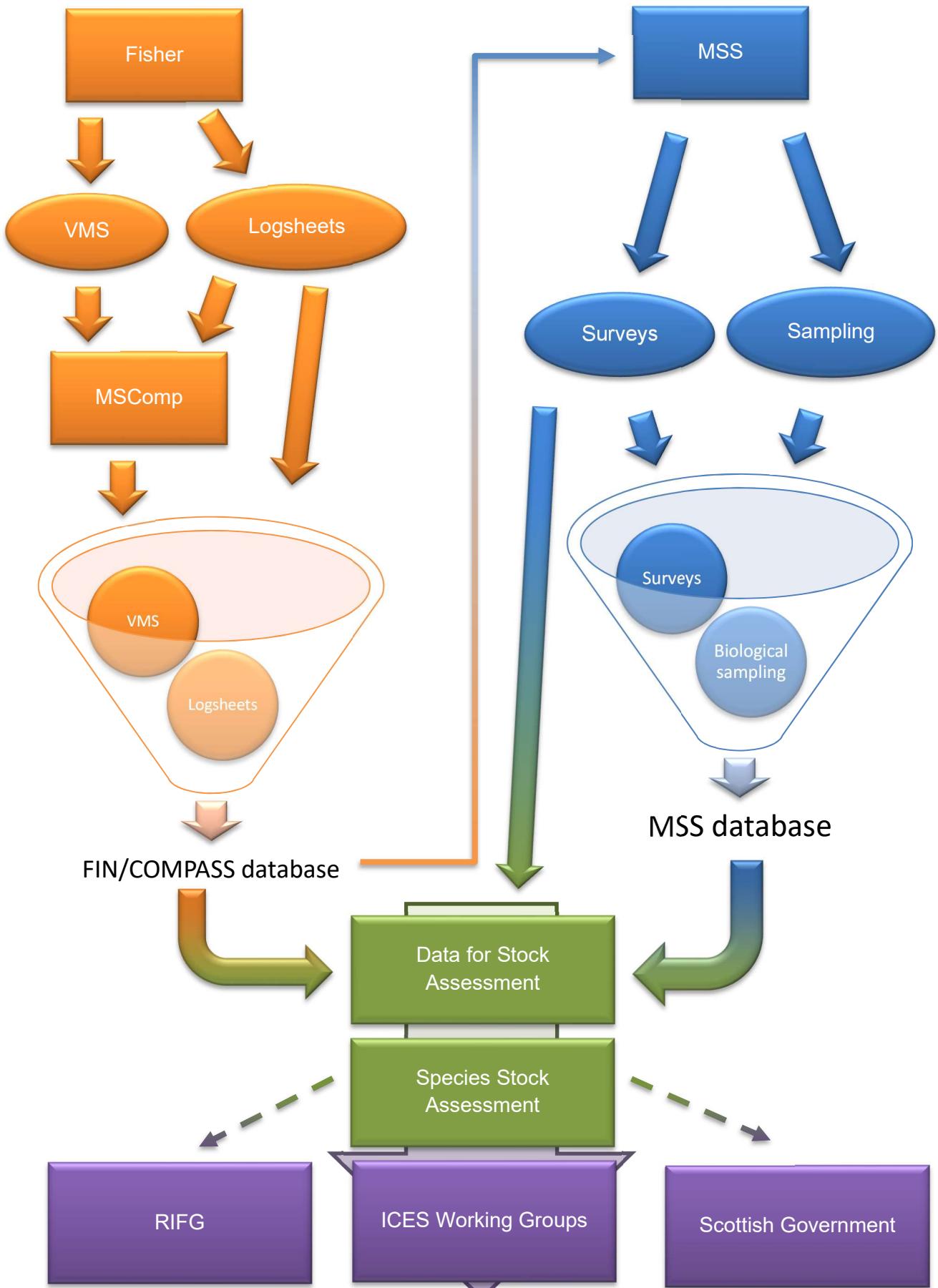


Figure 2.4 Diagrammatic representation of how the parts of the process and the data are linked together.

2.2 Stock Assessment Approaches

It is acknowledged that the current stock assessment process is not comprehensive, in some areas there is insufficient evidence to carry out stock assessments, and in other areas the frequency or spatial scale of assessments is such that they are not effective at a more localised management level (Miethe, *et al.*, 2016) for example for use by the RIFGs.

2.2.1 Crab and lobster

Assessments are performed at a regional level (by assessment area), for males and females separately, every three years, with the most recent assessment¹¹, on data from 2009 to 2012, reported in Mesquita, *et al.* (2016).

Crab and lobster, which cannot be aged, are most commonly assessed in the Scottish inshore fisheries using Length Cohort Analysis (LCA). This provides an estimate of the equilibrium fishing mortality. Complementary to this, yield-per-recruit analyses provide an estimate of F_{MAX} which is a proxy for F_{MSY} . For the purposes of the assessment landings data are used in conjunction with biological sampling data (averaged over a three-year period) to provide a raised annual landings-at-length distribution. A major assumption of the LCA approach is that the fishery is in a steady state condition:

“One of the fundamental assumptions of length-cohort methods that use length composition data is that the stock is at equilibrium, with no variation in exploitation over time and no variation in year-class strength. Under equilibrium conditions, length composition data will be stable over time.” (Chang and Megrey, 2010). Because, *inter alia* fishery landings are not constant over time, this assumption is not valid for Scottish fisheries.

Data for stock assessment purposes is considered to be well sampled from most areas, however this is not the case in Papa (brown crab and lobster), North Coast (brown crab), and South Minch (lobster) (Mesquita, *et al.*, 2016). In these areas, where samples are available, the length frequency data are similar to that in adjacent areas, and therefore the assumption is made that the data are the same. These assumptions have not been investigated with respect to the outputs of the assessment and therefore the recommendation is that the LCA results for these areas be interpreted with caution. There is no collection of discard data from crab and lobster fisheries, however discard survival rates are high and therefore the landings are assumed to represent all fishing mortality. A decision making matrix is used to determine whether or not it is viable to run a stock assessment and includes a set of criteria for each species and area (Table 2.4). An assessment is carried out every three years where the processing of sampling data allows.

Additional input data required for LCA are biological parameters such as length-weight relationships (taken from market sampling data), natural mortality (M), and the values of the asymptotic length L_∞ and the instantaneous growth rate K – these last two are estimated using Ford-Walford plots¹². The current assessment methodology applies the same biological parameters over all areas (with the exception of Shetland). There is no examination of the

¹¹ Further assessments have been produced, however these were not available to the authors at the time of analysis and writing of this report.

¹² In Shetland, area specific input parameters are used following the work of Tallack (2007b, c, a)

validity of this approach by Mesquita, *et al.* (2016), although the difference between parameters reported in Shetland is questioned.

The results of stock assessments for both brown crab and lobster are reported within the “*Fish and Shellfish Stocks*” series which is an annual publication produced since 2010. The 2016 version included data up to the end of 2014.

Table 2.4 Decision making categories and criteria for the assessment of crab and lobster (Mesquita, *et al.*, 2016).

Categories	Criteria
Whether or not the area had been assessed prior to 2006 to 2008	
The number of individuals/landings sampled	Poor: no sampling or very few individuals sampled (average <100/year) OK: Few animals sampled (average <500/year) Good: Several animals sampled (average>500/year)
The number of years available to produce an average length frequency	Poor: <2 years OK: 2 to 3 years Good: 4 years
The sampling seasonality (quarters)	Poor: <2 quarters sampled over the 4 year period OK: 2 or 3 quarters sampled over the 4 year period Good: All quarters sampled over the 4 year period
The shape of the Length Frequency Distribution.	Poor: No data or very few animals sampled OK: LF with some spikes Good: Approximately normal with no spikes

2.2.2 Scallops

Scallop stock assessments are reported in a separate publication, with the most recent available information based on the results of the 2016 assessments (Dobby, *et al.*, 2017). Prior to 2011 assessments used Virtual Population Analysis (VPA) but this has been superseded by a Time Series Analysis (TSA) approach incorporating biological data (Dobby, *et al.*, 2012). This method was deemed to be preferable to the VPA analysis (outlined below) for a number of reasons, including:

- It allows fishing mortality estimates to evolve over time in a constrained manner.
- The model provides precision estimates of estimated parameters (numbers at age and fishing mortality at age).
- It can cope with the omission of catch or survey data if data are of poor quality or missing.
- The model allows survey catchability to evolve over time.

Dobby, *et al.* (2017) state that the assessment is a state space approach which differs from the standard TSA model application by not including autoregressive or moving average terms.

Data collection for the scallop assessments is divided into assessment areas (Figure 2.3) which are derived from ICES statistical rectangles. Information from both dredge and dive fisheries is included. Fisheries data includes Scottish landings data (from UK vessels landing in Scotland) which is extracted from FIN and the MSS fisheries management database (FMD).

Scallop catches which have been taken in Scottish waters, but landed elsewhere in the UK, are obtained from the iFish Database for UK vessels (2011 to 2015), from the Marine Institute in Galway for Irish vessels, and Bangor University for vessels from the Isle of Man.

Data used in the scallop stock assessments included landings data from sales notes and EU logbooks (available from 2000 to 2010), catch-at-age data from the market sampling programme, and research vessel surveys carried out yearly at fixed stations which were chosen based on BGS sediment type and VMS data (see also Section 2.1.2). Length-weight relationships were used to convert stock assessment outputs in numbers to live weight and a natural mortality of 0.15 year⁻¹ was assumed based on data from other shellfish stocks of similar longevity (Cook, *et al.*, 1990). This permits the calculation of year specific weights-at-age using size-at-age composition information from market sampling. This allows for inter-annual variation in weights-at-age (due to changes in size-at-age) to be accounted for in the estimate of Spawning Stock biomass (SSB). Previously fixed values for weight-at-age were used.

Biological data are taken from the market sampling programme with no discard data available. The assessment states that the mortality of discarded scallops is low and therefore an assumption of zero discard mortality is unlikely to affect the overall reliability of the stock assessment. Length-weight relationships are incorporated in two ways, with a length total weight (including shell, gonad and muscle weight) is used as a raising factor for vessel landing data, while annual mean live weights at age are used to convert the numerical stock assessment outputs into a weight value.

Eight stock assessment areas are available for scallops but the data are regarded as insufficient for carrying out TSA or other stock assessments for three of these areas: the Clyde, the Irish Sea, and Orkney assessment areas (Dobby, *et al.*, 2017). The 2016 assessment was the first time sufficient data was available for the East Coast.

Virtual Population Analysis has previously been used for scallop assessments in the Scottish inshore fishery (and is still used as part of a suite of tools in the assessment of Shetland's scallop stocks), but has subsequently been replaced by the TSA methodology outlined above. Virtual Population Analysis is an age based method which can be used to estimate the biomass of the stock and to make predictions on yield and biomass based on different levels of fishing mortality. This method is useful in that it utilises catch data without making any underlying statistical assumptions (Hilborn and Walters, 1992). It does however require accurate information on natural mortality rates (M) and errors in the estimation of M can affect the outputs of the assessment. Ageing errors can also affect the outputs of the model, particularly where there are strong year classes present. Virtual Population Analysis also assumes that there is no net immigration or emigration from the stock, this may not be a substantial issue in terms of stock movement for scallops which are largely sedentary, but does not take into consideration recruitment to the population. To use the outputs of a VPA in setting reference points or management decision making, a time series of data would be required.

3 EXAMINATION OF EXISTING DATA AND CONSIDERATION OF ALTERNATIVE DATA COLLECTION AND STOCK ASSESSMENT APPROACHES

The data upon which this study was based was supplied by Marine Scotland Science and comprised two separate data sets, namely:

- a) crab, lobster and scallop biological data over the ten years from 2007 to 2016 inclusive.
- b) crab, lobster and scallops landings data over the ten years from 2007 to 2016 inclusive.

The biological sampling data (a) made available for this study for crab and lobster contained the variables:

Year, Month, Statistical Rectangle, Species Code, Trip ID, Gear Code, Landed Weight (kg), Sampled Weight (kg), Length (cm), Number-at-length, Gender, and Sample Category, i.e. the level of resolution is year x month x statistical rectangle x trip x species x gender x length x gear,

while the landings data (b) contained the variables:

Year, Month, Statistical Rectangle, Landings (kg), Species Code, Nationality, Fishing Method, Code, i.e. the level of resolution is year x month x statistical rectangle x species x gear.

There were confidentiality issues around providing vessel ID information to the study, hence the absence of these variables in the above two datasets.

3.1 Biological sampling

This section addresses the quality of the existing catch length structure data (for brown crab and lobster), with the objective of assessing whether the amount of sampling undertaken at present is adequate, excessive, or inadequate. If the amount of sampling is presently excessive or inadequate, the objective is to recommend the extent to which sampling can be reduced, or to which it should be increased. In order to be able to do this it is necessary to develop methods to calculate the sampling variance in length frequency data, and to assign components of this variance to different aspects of the sampling process, as is described here. It is also necessary to establish thresholds for data quality that are sensible in from a management perspective. The work described here is a key component of this document and response to the terms of reference.

3.1.1 *Quality of size structure data*

Technical Appendix 1 of this document describes the methodology used to calculate the precision of length composition estimates provided by the biological sampling programme. Briefly, the variance components of the available length frequency data were estimated using the R GLMER (Generalized Linear Mixed-Effects Models) routine, which runs GLMMs (Generalized Linear Mixed Model). The data were analysed at the level of resolution of fishing trip, and so the variance estimates that are provided are between trips. However, at an early stage of this work we found that, as one would expect, the variance of length from trip to trip is dependent on a number of factors. These factors included the statistical area, the month,

the year, the gender, the season and the assessment area. Over and above all those factors, the analysis was broken down into sample size bins, where sample size refers to the number of animals sampled on a trip. In most cases, it emerged that the trip to trip variance is relatively large when the sample size is small, but that it declines as the number of animals measured per trip increases. It then tends towards an asymptote at very large sample sizes, as one would expect, when there is no more benefit to be obtained from increasing the sample size further, but the inherent variability due to trip cannot be reduced and remains present.

Numerous technical challenges were encountered in carrying out this work. As the data were analysed using the GLMER routine with a binomial distribution and logit link function, the interpretation of the resultant variance components at the original length proportion scale required the development of a scheme for conversion between logit and length proportion scales. This scheme is described in the appendices. Furthermore, since the estimation of the effect of sample size on the variance components involved binning the data into different trip sample sizes, the subsequent requirement to determine optimal sample size meant that a smooth relationship between variance and sample size had to be made available. This made it necessary to fit smoothing functions to the relationship between variance components and sample size, where sample size was represented by the average sample size value for each sample size bin.

Given the availability of data for a number of species, years and assessment areas, a large number of results were produced. These results fall into the following broad categories

- a) Variance component estimates,
- b) MWCV (Mean Weighted Coefficient of Variance) estimates for the historic data,
- c) An assessment of whether in the historic period the 20% or 30% MWCV has been achieved, where and when, and
- d) A variety of tables and graphs relevant to optimal survey design.

These results are presented in some detail in Technical Appendix 4.

It is important to appreciate the scope of the conclusions derived from the methods and data available for this section. The data made available to the authors did not contain any information about subsampling methods, therefore it was not possible to draw conclusions about the variance due to particular subsampling approaches. Sub-sampling in this context means the way that samples are drawn from a trip for purposes of measuring the length (for example) of animals that are landed.

Table 10.13 and Table 10.14 provide a retrospective assessment of annual MWCVs for 2007 to 2016 for lobster, Table 10.15 and Table 10.16 provides the same for crab, while Table 10.17 provides results for scallops. Table 10.18 summaries which stocks attained MWCVs of either 20% or 30% over the last five years for lobster and crab, while Table 10.19 is the same assessment for scallops.

Present retrospective estimates of the MWCVs for lobster for either double the number of trips or double the sample size per trip. Table 10.30 and Table 10.31 are the same results for crab, while Table 10.32 and Table 10.33 gives the results when these options are repeated for scallops.

3.1.2 Alternative sampling designs

In view of the fact that a considerable portion of this document is directed at assessing the efficacy of the present biological sample programme, and the statistical reliability of the data collected to date, it is important to keep in mind that whatever new data collection technologies are introduced, the sampling design used to operationalise these new technologies would be subject to many of the sample design considerations that are dealt with in this report. It is implicit in the introduction of new data collection technologies that more sampling is better. The results presented here suggest that qualification of what is meant by “more” is required. This may or may not be relevant to a given technology, depending on cost and mode of implementation. For example, camera and/or video technology can be expensive, and may only be introduced on a few vessels with defined technical requirements.

The results presented in Table 10.20, Table 10.21 and Table 10.22 provide a basis for estimating how many trips would have to be sampled to achieve an MWCV of 30%. These results can be used to estimate how many vessels would need to participate in sampling. Further results with additional options can be found in Appendix 4 and are not repeated here.

An important result detailed in Technical Appendix 4 is that instances of low sample size in the historic record increases the MWCV substantially for both lobster and crab. The causes of low sample size per trip need to be properly understood before clearly recommending specific remediation. We do not know, for example, whether the occurrence of low sample size is due to

- a) Low catches, so that even though the entire catch was sampled, sample size is low
- b) Low proportions of species in catches, so that the random sample that was drawn contained a small number of animals for the species of interest.

Remediation is different depending on whether (a) or (b) are the factor determining low sample size:

If (a) then in order to mitigate this problem, consideration of sampling vessels with larger catches must be contemplated.

If (b) then oversampling of species which do not show sufficient sample size in the usual random sample that is drawn is required.

If there is no possibility to mitigate either (a) or (b) as suggested above, then the only way to achieve a desired level of precision for catch length frequency estimates is to increase the number of trips that are sampled. In circumstances where the sample size per trip cannot be controlled to achieve a design level, it is recommended, particularly for lobsters, that the threshold for the MWCV calculated via the methods set out in Technical Appendix 4 be set at 15%, and not 30%.

3.1.3 Recommendations for improvements to biological sampling

We note that in the following, recommendations for all sample sizes for lobster and crab are ‘per gender’ and for the size range used in the LCA calculations. Data from the Shetland and Irish Sea management units have not been included as they have a different minimum landing size compared to other management units, and hence a unique sampling size range. Our

approach of pooling data across all management units meant that these particular units were excluded from the analyses.

In order to formulate recommendations for improvements in sampling approaches for lobster, we consider the results in Technical Appendix 1 Table 10.23 (the comparison between idealised MWCVs and empirical MWCVs for 2016), and Table 10.20 and Table 10.26. The idealised MWCV calculations are either with or without consideration of the effect of month/statistical area variance components. Taking 30% as a target MWCV, and provided that the sample size per trip can be controlled at no less than the sample sizes shown in Table 10.23, then the design MWCVs are applicable and achievable. Under these circumstances stocks from the Clyde and North Coast were not meeting the 30% threshold in 2016. This is clearly because there was only one trip sampled in both those areas in 2016. These conclusions are not much changed when adjusting (roughly) for time/area variance components.

- 1) In order to meet the 30% threshold at Clyde, for the same number of individuals sampled (ten for females and 16 for males), the number of trips needs to be increased from one to between five and ten trips per year.
- 2) In order to meet the 30% threshold at North Coast, for the same number of individuals sampled (34 for females and 14 for males), the number of trips needs to be increased from one to between three and ten trips per year.
- 3) It is not feasible to reach the 30% MWCV threshold at either Clyde or North Coast by increasing the sample size per trip, although this is possible if three trips are sampled and the sample size per trip per sex is increased to at least 30 each.

Clearly whether these additional samples are feasible depends on the value of the fishery. In addition to the recommendations made above to increase sampling in certain areas, it seems that sampling can be reduced at South Minch (moderately) and Orkney (substantially), and this may be an opportunity to save costs in trying to improve sampling at Clyde and North Coast.

For crab, a 30% threshold is not being achieved at the following: Clyde, South Minch and Ullapool. Table 10.24 (the comparison between idealised MWCVs and empirical MWCVs for 2016), and Table 10.21 (idealized MWCV calculations without consideration of the effect of month/statistical area variance components, for crab these variance components are negligible) are relevant to recommending reforms to achieve better results at these areas.

- 1) In order to meet the 30% threshold at Clyde, about five trips need to be sampled for crab, and no trip should sample less than about 40 crabs per sex (within the LCA size range).
- 2) In order to meet the 30% threshold at South Minch, for the same number of individuals sampled (30.5 for females and 39 for males), the number of trips needs to be increased slightly (the design results suggest from about six trips, to be safe, about nine trips).
- 3) At Ullapool, the number of trips needs to be increased to about five trips (from three). The sample size per sex and trip should not be less than 76.

For crab, excessive sampling is taking place at the following locations: East Coast, Hebrides, and Orkney and a reduction in the sampling at these locations (especially the number of trips sampled) may offer an opportunity to increase the amount of sampling at Clyde, South Minch and Ullapool. Although the data reflect a sampling level of 11 trips for crabs in 2016 for North Coast, only one trip was sampled for lobsters. Thus while the results for 2016 for crab suggest that a reduction in sampling effort could be contemplated at North Coast, the year 2016 seems anomalous for North Coast and so this is not a recommendation made here.

For scallops, without taking consideration of adjustments for month and statistical area components of variance, the 30% MWCV threshold is not being achieved at Clyde and Orkney (for 2016). Achievement of an MWCV of 30% cannot be achieved by increasing the sample size of scallops per trip above the amounts achieved in 2016, and should instead be achieved by increasing the number of trips sampled at Clyde from three, to between five and ten. The same applies for Orkney.

We note however that the ad hoc adjustments made here to account for month and statistical area components of variance suggest that additional areas would, on these calculations be failing to achieve the $MWCV = 30\%$ threshold. On examination of Table 10.27 it appears that because of the large number of samples per trip, no additional areas fall within the definition $MWCV > 30\%$, therefore this particular adjustment does not lead to a recommendation to increase sampling in any of the areas other than Clyde and Orkney.

3.2 Alternative stock assessment methodologies

3.2.1 Crab and lobster

In view of the likely proposal that the collection of biological data can be partially automated and could therefore be increased in “volume”, it was felt important to gain some insight into the value of an increase in the “volume” of length frequency information for the estimates provided by the LCA method.

Technical Appendix 2 reports on the results of a simulation analysis of the bias in LCA for estimating fishing mortality. It uses two different data generation schemes, referred to as “Simple” and “Dynamic”:

“Simple” most closely matches the implicit assumption in LCA, that the population is at equilibrium and that recruitment occurs as a continuous year-round process.

“Dynamic” is the situation where there is variance in length-at-age, recruitment occurs in one or more pulses during the year, and equilibrium may not necessarily hold.

The simulation method is used to explore the bias in fishing mortality estimates when the biological parameters assumed for LCA differ from the true values, or when the equilibrium assumptions do not hold. Four different approaches to calculating terminal fishing mortalities are explored, two of which involve iterating the terminal fishing mortality on the assumption that selectivity in the largest four length bins are equal.

The information provided in Technical Appendix 2 includes a summary of the biological parameters for the lobster and crab stocks considered.

In order to assess the potential for bias in LCA based fishing mortality estimates using either the dynamic or simple data generation approaches, a range of options were explored. These are described in Table 11.3 for the “Dynamic” data creation situation and Table 11.4 for the “Simple” data creation situation.

The “Dynamic” options involve the following:

- A base case in which the biological parameters assumed for the LCA analysis match those used for data generation
- Introduction of error in the estimate of the proportion caught at length
- Use of M in LCA which is 50% larger than used for data generation
- Use of a growth rate parameter in LCA which is 50% larger than used for data generation
- Three difference ways of setting the terminal fishing mortality value
- Use of different values of the variance in length at age.
- Spawning throughout the year (Y) or only once at the beginning of January (N).
- All cases are repeated using time varying values of fishing mortality.

The “Simple” options involve a base case option in which the LCA assumptions match what is used in for data generation, then three different ways of calculating the terminal fishing mortality are explored, followed by an option in which the LCA value of M is 50% larger than used for data generation, and then an option in which the growth rate parameter K for LCA is 50% larger than used for data generation.

The results of bias in the LCA based fishing mortality estimates are presented as follows:

The “Dynamic” results for crab are shown in Table 11.5, Figure 11.1, and Figure 11.2, and the “Dynamic” results for lobster are in Table 11.6, Figure 11.3, and Figure 11.4.

The “Simple” results for crab are shown in Table 11.7, Figure 11.1, and Figure 11.2, and the “Simple” results for lobster are in Table 11.6, Figure 11.5, and Figure 11.6.

Results of the LCA bias investigation shows that the most serious bias is due to a failure of the equilibrium assumption. This is clearly shown by the comparison between Options 1 to 9 and 10 to 18 of Tables 11.5 and Table 11.6, for the dynamic data generation simulations. Options 10 to 18 are the options based on a trend in fishing mortality. Note that the dynamic data generation process does not match the assumption underlying the LCA because for the LCA recruitment happens in pulses at the beginning of each of the 12 calendar years, whereas LCA is based on a continuous and constant recruitment assumption, and because there is variance in length at age in the dynamic data generation process, while LCA assumes that there is a one to one relationship between age and length.

Within Options 1 to 9 of Tables 11.5 and Table 11.6 there is still some bias. In the first instance the base case model (Option 1) shows bias depending on how the terminal fishing mortality value is set. Results for Options 2 to 9 should then be viewed relative to these biases. The additional effect of adding sampling error (Option 2) is to increase the negative bias in fishing mortality estimates slightly. Option 8 involves reducing the variance in length at age from a standard deviation (SD) of eight to a SD of five. This substantially reduces the bias, indicating that the inclusion in the dynamic model of variance in length at age is an important contribution to bias in the LCA in general.

It is not surprising that Options 3 and 4 for which the LCA uses either a natural mortality value or a value of the growth rate parameter which is 50% too large, increases bias. However, it is

moot as to whether these particular sources of bias would result in biased management, since these two factors would also affect the yield per recruit analyses which are used to estimate target fishing mortalities.

The results for Option 5, 6, and 7 show that it is important to pay attention to exactly how the terminal fishing mortality is set in the LCA, since different approaches lead to a different scale of bias. However, this is complicated since no clear recommendation emerges as the best approach across the assessment areas.

For the simple data generation results the biases are much smaller than they were using the dynamic data generation process. Only six options were explored, a base case, three difference approaches to setting the terminal fishing mortality, and the use in the LCA of M or K values that are 50% larger than the values used for the simulations. Unsurprisingly, as for the dynamic results, use of the incorrect value of M or K amplifies the extent of bias. Differences are also seen across the different approaches used for setting the terminal fishing mortality value.

3.2.1.1 Integrated assessment approaches

Over the last few decades methods such as LCA have, for certain stocks, given way to more generally formulated methods such as are described in Bergh and Johnston (1992); (Punt, *et al.*, 2013) and Haist, *et al.* (2009). These approaches integrate catch-at-length data and CPUE data (see for example Fournier and Archibald, 1982). This has, over time, resulted in further generalisations to include most other kinds of fisheries related data that can be collected, whether fisheries dependent or independent, including survey data and mark-recapture data. The method is scalable in that a very broad range of data types can be added to the analyses over time as new data types become available. In addition, the methods are flexible in that various assumptions can be imposed or relaxed. In the context of the application of LCA to crab and lobster stock assessments, the LCA method can be set up in Integrated Analysis (IA) as a particular contraction or simplification of the IA method. However, since the IA is based intrinsically on a more general view of populations dynamics, one can then relax the equilibrium assumption in the IA (as adapted to work like LCA) to explore the consequences of allowing for stock dynamics. The impact of minimum size, variance in growth rates and differential fishing selectivity between different sectors of the fleet, or surveys, can all be modelled using IA.

Although IA can work with any data (or purely from assumptions, in extremis), it is recommended that for management purposes IA is only applied when it includes a population abundance index, either from surveys, or from CPUE data. The method is therefore only regarded as potentially reliably applicable under circumstances that a survey abundance index, or perhaps a CPUE index related to resource abundance is available.

It is likely that a switch to the use of integrated stock assessment models will open up a discussion about the reference points in use for management purposes. For example, for Scottish inshore crab and lobster stocks, the use of F_{MAX} as a management target works well in combination with the LCA method (which provides an estimate of recent average fishing mortality). The integrated stock assessment model approach would however produce a range of additional outputs which might support a management approach or a control method which

is not presently a feature of the management and control of the Scottish inshore stocks of crab and scallops.

The main drawback of the integrated length-based methods just mentioned is their greater complexity and their reliance on the availability of specialist skills, although this problem can be mitigated by making use of the many available freeware packages available that can be tailored to run such models (see Dichmont, *et al.*, 2016 for an overview). In principle however there are no other inherent obstacles to their use in the context under consideration, i.e. the Scottish inshore fisheries for crab and lobster. The methods are scalable in the sense that they can be implemented in very simple terms using only catch-at-length data, but can be scaled up gradually over time to incorporate other data types such as CPUE and others (survey, mark-recapture).

3.2.1.2 Stock Assessment Methods which use Catch Per Unit Effort (CPUE)

The main additional data types that can provide insight into the dynamics of a resource when catch-at-age data are not available, as is the case for the Scottish inshore lobster and crab stocks, are CPUE data, survey data (abundance indices and associated population length and sex structure data), and mark-recapture data. Considering initially CPUE data, the shortcomings of these data should not be ignored and are well known. These are their susceptibility to effort creep, to biases due to differential targeting strategies in multi-species fisheries, and to the tendency in some stocks for CPUE levels to hold-up despite declines in resource abundance, known as hyper stability. Despite these shortcomings, it is likely that CPUE data are better able to provide an indicator of trends in stock abundance than are catch-at-length data. Assuming that such trends are relevant to fisheries management, methods that allow a time series of these data to be included in stock assessments need to be considered.

The most common methods that make use of catch and CPUE data are dynamic pool models. However, given that the dynamics of the Scottish crab and lobster stocks involve a number of important length dependent processes including fishing selectivity, minimum size and possibly sexual dimorphism in natural mortality and growth, it is worthwhile considering stock assessment methods that reflect size based dynamical features, while at the same time permitting the incorporation of CPUE data. Methods that are able to simultaneously model catch, CPUE and catch-at-length are the class of size based assessment methods described by Bergh and Johnston (1992) and Haist, *et al.* (2009).

This project is aware that there are limitations on the availability of CPUE data for the stocks under consideration in the Scottish inshore fisheries. This is due to the absence of detailed effort information (number of creels hauled per day) for all assessment areas other than from Shetland. Technical Appendix 4 of this document proposes methods making use of daily landings data as a proxy for LPUE, based on detailed creel haul information. This proxy method is validated in this document using the data for Shetland (see also Technical Appendix 4). Briefly, for Shetland, we obtain very high correlations between the year effect from GLMs which use the LPUE (as daily landings/creels hauled) and the daily catch (as a proxy for LPUE) (see Table 3.1).

Table 3.1 Output of GLM analysis for data held by the SSMO, Shetland, on lobster and crab landings with and without anonymised vessel identities.

Model	With vessel ID		Without vessel ID	
	Correlation	R ²	Correlation	R ²
Both species	0.98046765	0.96131681	0.97977060	0.95995044
Lobster only	0.99369174	0.98742326	0.98490165	0.97003126
Crab only	0.97351890	0.38665680	0.97754539	0.95559499

This suggests that there may be value (i.e. possible new insights) to be obtained from carrying out General Linear Models (GLMs) of daily landings records for other parts of the inshore fishery in Scotland to estimate resource abundance trends. Statistically significant trends, either increasing or decreasing over time, indicate that the equilibrium assumption of the LCA method is not valid for those cases.

Some initial feedback received during this work package about the proposal to use daily catch information as a proxy for CPUE was that this is likely to be biased by systematic trends in the number of creels hauled per vessel. Some further statistical analyses were carried out for Shetland to estimate whether this might be a problem, and the key results are as shown for crab and lobster in Figure 13.4 and Figure 13.5. Although these results do reflect some increase in creels hauled per year per vessel, the extent of this increase is small. The conclusion is that the calculation of standardised daily catches as is described in Technical Appendix 4 is worthwhile, and could be used in the context of sensitivity tests to a small and systematic increase in the creel pull rate per vessel.

3.2.1.3 Assessment areas

It is necessary to gauge whether existing data have sufficient spatial resolution in the event that different, and possibly smaller, spatial areas are chosen as stock assessment areas, or perhaps as management areas. At the present time the stock assessments for crab and lobster are carried out using the assessment areas described in Figure 2.2 (also see Mesquita, *et al.*, 2016), however these areas do not match the management areas covered by the RIFGs, or the jurisdictions of the Marine Planning Partnership areas into which RIFGs may input, nor do they provide data at a fine enough spatial resolution to facilitate spatial management measures within RIFGs. Food and Agriculture Organization (FAO) precautionary guidelines indicate preference for smaller assessment and management areas when there is uncertainty between that and larger areas for the unit stock definition. This is a particular consideration for sedentary species, where a precautionary approach would be to assume that recruitment is unique to comparatively small areas, the size of such areas decreasing as the sedentarity of the species increases. Assessments for crab and lobster are carried out using the 12 assessment areas outlined in Figure 2.2. The smallest spatial resolution for data collection is presently an ICES statistical rectangle which is smaller than the assessment area. It would seem that data for smaller assessment areas is accessible in principle and could be produced should this be required at some stage in the future; hence this possibility is covered in principle by the existing sampling schema.

3.2.2 Scallops

The assessment of scallop stocks is carried out via a completely different methodology than for lobster and crab, viz the time series analysis (TSA) approach in the case of scallops and

the length cohort analysis (LCA) approach in the case of lobster and crab. The data that are used for TSA are far superior to those provided for LCA, and include catch age structure information and survey abundance information which is age class disaggregated. These data are highly rated and informative about resource dynamics and there was no reason to question the assessment approach or its input data. Issues of bias and variance are always of concern. However, the simulation testing of TSA for scallops to establish a link between critical assessment outputs such as F based reference points fell outside the scope of this study. This was partly but not only due to the fact that TSA is presently run using NAG software which is proprietary software and not freeware. Another reason was the relative complexity of the TSA approach compared to LCA.

3.2.2.1 Integrated Analysis (IA) vs Catch-at-Size Analysis (CASA)

For Scottish scallop stocks, the two main alternative approaches that could be considered are

- a) general Integrated Analysis (IA) approaches which, much like the dynamic size based assessment methods, admit a very broad range of data types – these include all data that are presently used in the TSA based stock assessment analyses, and
- b) the Catch-at-Size Analysis (CASA) approach used in the northeast of the USA.

There does not seem to be any purely estimation based advantage of IA over TSA, and TSA is superior to CASA since it uses catch-at-age information. The main benefit of IA is its wider use across a number of stocks and jurisdictions around the world (for example, South Africa, USA, Australia). This means that the skills required for the implementation of IA may be more readily available, and the method more widely understood. Beare, *et al.* (2005) noted that a shortcoming of TSA is that there is not yet a robust and general version of the code available, and the number of practitioners experienced with TSA is very limited. For these practical reasons we recommend consideration of the application of IA.

The results of integrated stock assessment analyses should only be applied for management if the input data contains at least one index of abundance, either CPUE data from catch and effort log as reported by fishers, or an abundance index from fishery independent surveys. Failing that, IA may nevertheless be a valuable exercise because attempts at its application would highlight gaps in data gathering and help to formulate data priorities. The most obvious fisher led data that IA would potentially require is CPUE data, however as stated elsewhere in this report, the strength of IA is really in the word “integrated” – the approach has the potential to integrate all existing and future data types. It can therefore consume any data that are made available by fishers, but of course some triaging is appropriate depending on the quality of the data.

In the northeast USA scallop fishery the current stock assessment approach is size based, CASA. In Scotland, the TSA approach is considered more appropriate and is carried out in half of the eight king scallop assessment areas (Figure 2.3). The use of TSA in the Scottish inshore fisheries is superior to CASA because it uses age-based data from the fishery (i.e. catch-at-age) and from surveys (catch-age indices). Age-based information, provided biases and sampling variance are limited, is far more informative than length-based information.

3.2.2.2 Spatial resolution of assessments

The relatively sedentary nature of scallops raises some unique challenges and possibilities. For example, it seems likely that scallop stocks are not at all well mixed within assessment

areas or even within subsets of assessment areas. While this is obviously an important economic consideration from a fleet management perspective; vessels ideally need to have the ability to be able to target recently relatively unfished locations, similar considerations apply to the interpretation of fisheries dependent and independent data. Looking to the future one must anticipate greater demands being placed on relatively fine scale spatial catch and effort information, for inclusion into fleet management systems, and also for use in stock assessment models (although such models are clearly still some way off).

3.2.3 Optimisation of Assessment Resources

When considering different approaches to data collection and stock assessment approaches it is important to consider the management context. How frequently should assessments take place and what data do they require in order to facilitate relevant to management.

Assessments can be separated into two types distinguished by whether or not they are based on a purpose or on their data requirements, these can be termed 'strategic estimation' and 'tactical estimation' (Punt, 2008; Bentley, 2015) (see Table 3.2). Bentley (2015) suggests that both mechanisms can be used at different frequencies to support management, with strategic assessments carried out every five years to evaluate management procedures and tactical assessments carried out each year to provide 'methods for regularly, efficiently and robustly using data to inform management decision making'. As this process progresses and data are added to the system the nature of the assessments can move from those more suitable to a data limited system, towards more complex assessment techniques. This approach could be relevant to Scottish Inshore fisheries where resources are limited for the collection of new data, and where there may be time constraints on accessing data. Carrying out a more straightforward tactical estimation on an annual basis could provide regular timely outputs upon which management decision making could be based. These outputs could be tailored to individual management units (e.g. RIFGs or Marine Planning Partnership areas). These would be backed up by a less frequent strategic estimation which would provide more detailed outputs, perhaps relying on a time-series of data. These could be built on the current stock assessment processes and would be linked to stock units or assessment areas.

Table 3.2 A comparison of the characteristics and roles of strategic and tactical fisheries estimation (from Bentley, 2015).

Strategic estimation	Tactical Estimation
Comparatively....	
More complicated	Less complicated
More integrated	Less integrated
More statistical	More empirical
Focus on estimating....	
Stock status (e.g. B_t/B_0)	Current biomass (e.g. B_t)
Reference points (e.g. B_{msy})	Current exploitation rate (e.g. F_t)
Parameter uncertainty	Forecast biomass(e.g. B_{t+1})
Within the management procedure approach provides....	
Distributions of operating model parameters and current state to define a plausible range of states of nature	A component of management procedure for inferring current fishery indicators from monitoring data

In considering the most suitable stock assessment approach for crab, lobster and scallop stocks it may also be useful to consider the detailed approach taken in the USA (see for example Mace, 2001) which defines five levels (referred to as the Stock Assessment Improvement Plan (SAIP) levels) of stock assessments, i.e.:

- 1) Assessment based on empirical trends in relative stock abundance (e.g. CPUE);
- 2) Assessment based on a snapshot equilibrium calculation (e.g. LCA);
- 3) Assessment based on time series of catch and an abundance index to support application of a dynamic model;
- 4) Assessment is age-structured, so needs time series of age and/or size data and can now estimate changes in fishery characteristics over time and can estimate fluctuations in annual recruitment, and has direct information on the fishing mortality of each year class entering the stock;
- 5) Assessments linked to ecosystem, habitat, or climate factors to help explain and forecast the fluctuations that are empirically measured in a level three or four assessment.

This is relevant to Scottish shellfish stocks which span a wide range of data availability and quality and therefore a range of stock assessment and management approaches are relevant. This checklist approach provides an example of a structure method to deciding the assessment and management approach, given that not all stocks can be analysed at an IA or dynamic size based levels given limited resources and insufficient data.

Mace, *et al.* (2001) notes that assessments at level three are generally considered able to determine overfishing and overfished status, but are not very useful for forecasting the impact of changes in annual catch limits. The authors noted that several different modelling approaches were in use, but that over time they had moved towards models that were age-structured internally but very flexible in their data requirements.

A Draft Protocol for Prioritizing Fish Stock Assessments (NOAA, 2014) makes use of the levels defined by Mace, *et al.* (2001), and a range of other inputs, indicators and proposed

procedures (see also Methot Jr, 2015 who covers similar ground). The prioritisation can be divided into “Target Assessment Level and Frequency” and “Prioritise to Achieve Targets”.

Target Assessment Level and Frequency is a determination of the SAIP level of assessment appropriate for a stock and the appropriate assessment frequency, whether annually, biannually, or multi-annually, involving the following considerations:

- Among unassessed and previously assessed stocks, set medium-term assessment goals.
- Among stocks that have never been assessed, set priority for first-time assessment, if any, or conclude that current level of baseline monitoring is sufficient.
- For stocks that need assessment, set target assessment level (i.e. SAIP); this drives the data requirements.
- Set target assessment update frequency for each stock.

Prioritise to Achieve Targets is a prioritisation step governing the distribution of stock assessment resources amongst stocks. This second process is dynamically updated as circumstances change over time, and it involves the following (summarised in Figure 3.1a):

- Benchmark assessments for those assessments needing improvement or for which new data will allow advancing to higher level;
- Update assessments for stocks that are at or exceed their target update period.

The process of prioritization to achieve targets summarized in Figure 3.1b, taken from NOAA (2014).

Setting of assessment target levels and frequencies is an initial step that is updated occasionally, but not annually (Figure 3.1a). The annual assessment priorities (Figure 3.1b) are designed to establish the goals of comprehensiveness and timeliness to be achieved by an assessment. Figure 3.1a refers to Productivity-Susceptibility Analysis (PSA), Vulnerability and Only Reliable Catch Stocks (ORCS) evaluation criteria for the assessment of targets and priorities. Previously unassessed stocks need a quick examination to determine which of these can stay at an unassessed level, which can be adequately tracked with simple baseline monitoring, and which need a first time assessment. Two recently developed tools recommended by NOAA (2014) to assist with this task:

- 1) The PSA (Patrick, *et al.*, 2010) produces a score that ranks stocks according to their vulnerability to being overfished, and hence in need of assessment.
- 2) ORCS, a data-poor approach (Berkson, *et al.*, 2011) is a tool that looks at available information regarding catch, other species in the fishery, and simple indicators of trends in stock abundance. It evaluates whether recent exploitation rate is light, moderate, or heavy; then provides advice on an Annual Catch Limit that should prevent overfishing until a more complete assessment can be completed.

Berkson, *et al.* (2011) documents the attributes that are considered in the ORCS schema to assign a stock status of lightly exploited, moderately exploited, or heavily exploited, but does not go into detail about the allocation of catches.

The priority for the first-time assessment of stocks can then be based on the PSA’s biological vulnerability to overfishing, the ORCS’ information on fishery impact level (stock status), and fishery and ecosystem importance. These two scores are added to a fishery importance score and an ecosystem importance score to obtain an overall score. Where data to implement PSA

and ORCS are lacking, expert judgment is required. The result will be a set of scores within a region to rank stocks according to their need for a first time assessment. Some of these will show a high need, but sufficient data to conduct the assessment may be lacking. Others may have sufficient data for an assessment, usually because data have been collected by a multi-species sampling program that provides data on all encountered species. Some species will score low on this scale, so have low priority for immediate assessment. They should not be ignored. Baseline monitoring to the extent feasible should continue and PSA and ORCS should be updated on a five to ten-year basis.

For stocks that have been previously assessed it is necessary to determine the target assessment level and frequency. The following factors are considered for this:

- 1) Fishery importance - i.e. commercial and recreational value to the regional fishing communities.
- 2) Ecosystem importance - role of the stock in the ecosystem and strength of its interactions with other species.
- 3) Stock status - relative to target and limit levels of abundance and fishing mortality.
- 4) Stock biology - how much change is expected per year, on average.
- 5) History of assessment - including availability of new information to resolve extant issues or indicate a change in stock abundance.

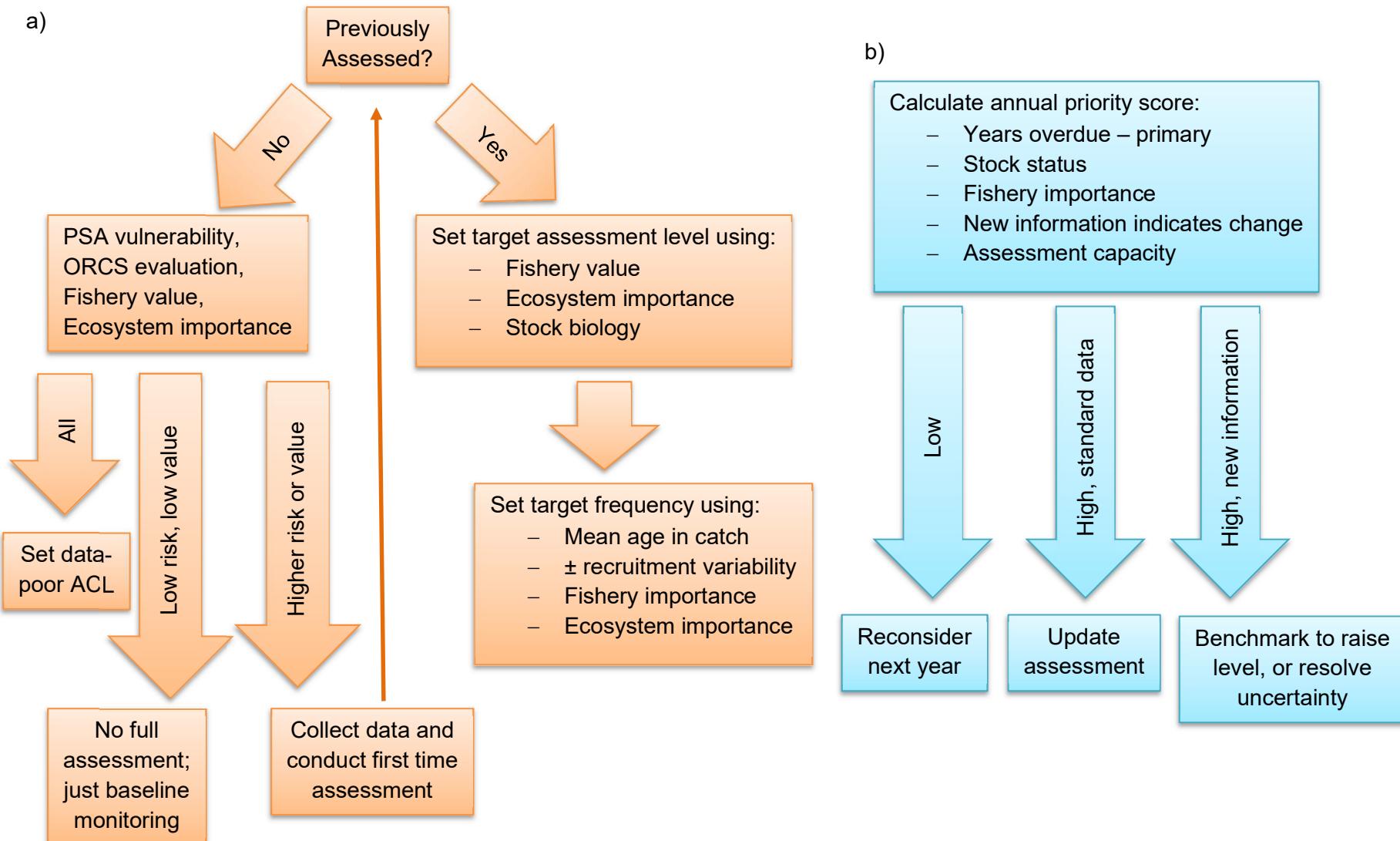


Figure 3.1 Flowcharts showing a) the steps for setting of assessment target levels and assessment frequencies and b) steps for setting of annual assessment priorities (taken from NOAA, 2014).

An explicitly numerical approach is then implemented (see NOAA, 2014) to derive an aggregate importance score to guide decision making on the assessment level, frequency, and annual priorities for assessments, as is now described briefly:

NOAA (2014) stated:

"After a stock has been assessed once, there should be enough information available to evaluate medium term goals for future assessments. Ideally the goal would be stated in terms of a desired degree of statistical confidence in assessment results. While many assessments present results with confidence intervals, the methods are too diverse to support direct comparison and all are not yet able to incorporate the effect of changing ecosystem factors on uncertainty in assessment results.

Consequently, a simpler approach is to establish a target for the comprehensiveness (level) of each assessment, and a target frequency for updating the assessment.

Level and frequency are considered separately because the types of resources needed to accomplish them are quite different. Increasing the level of an assessment generally requires acquiring a new kind of information. For example, going to an age-based assessment requires routine collection of data on fish ages. Addition of fishery-independent survey is another type of investment that can improve assessments. Increasing the frequency of assessments does not require new kinds of data, but does require addressing bottlenecks that impede conducting more assessments each year. For example, these bottlenecks could be more age readers to process existing age samples more quickly, more scientists to simultaneously work on more assessment updates, and/or better assessment standardization to streamline the assessment review process."

NOAA (2014) seems unable to prescribe the target assessment level appropriate for a given stock and refers back to Mace, *et al.* (2001) noting that further revisions of the SAIPs are underway to provide a more reliable description of the present state of an assessment. Then a prioritization process will be implemented to provide advice as to whether the current SAIP level for a stock is appropriate or whether improvements are required.

Fishery importance and ecosystem importance should affect the target frequency of assessments because of the improved fishing opportunity obtained by quickly tracking upturns in stock abundance, and conversely the fishery and ecosystem risk avoided by preventing acceleration of downturns.

3.3 Indicators

A recent review carried out by Miethe, *et al.* (2016) has reported on a wide range of potential indicators for shellfish stocks and fisheries. These include abundance, spatial and size based indicators, reproductive and morphological characteristics and indicators based on fishers' knowledge. The work of Smith (2008) also provides a great deal of very useful information regarding the potential use of a range of indicators including their potential application in UK capture shellfish fisheries. It is not intended to replicate the work of either Smith (2008) or

Miethe, *et al.* (2016) here; however, indicators which could be facilitated by fisher led data collection programmes are discussed.

The use of indicators as a management tool is often advocated in data deficient fisheries, as they can be derived from more limited data sets than those required for a full analytical stock assessment. They can also provide a useful, and accessible mechanism for fisheries managers to interpret biological changes in the population in a more transparent way when compared to the interpretation of outputs from models.

Reference points are a mechanism by which indicators and their underlying biological data can be integrated into fisheries management. There are a number of different methods by which this can be achieved and these will depend upon the type of indicator, the quality of the data, the management aims to be fulfilled, and the management mechanisms (e.g. harvest control rules, regulations, governance).

The report by Smith (2008) provides a background to potential reference points for shellfish fisheries. It states that in order to be most useful biological reference points should:

- Be based on well-estimated parameters.
- Have stable characteristics and be durable.
- Be tractable and have manageable data requirements.
- Be transparent in both their definition and application.

There are two main types of reference point which refer to a desirable status of the fishery or management aim (Target Reference Point) to be attained, and an undesirable status (Limit Reference Point) to be avoided (Caddy and Mahon, 1995). Reference points can be based in relative (e.g. changes based on data from previous years) or absolute terms, or can also be directional (e.g. an increase or decrease in a specified value). It is acknowledged that the setting of target and limit reference points, while being technically informed, is to a certain extent an arbitrary process of risk assessment (Caddy and Mahon, 1995).

Hilborn (2002) suggests that data-based mechanisms within harvest control rules (as opposed to those derived from modelling), for example the use of CPUE indices, may be more appropriate than traditional reference points such as absolute abundance, virgin biomass, and reference exploitation rate; which are inherently difficult to estimate. Data-based rules have the benefit of being simple to apply and they are transparent in both their definition and application as advocated by Smith (2008) and are empirical rather than estimated in their nature (Kelly and Codling, 2006), both qualities appropriate to fisheries which may be lacking in data for analytical assessments. Data-based rules can also incorporate conservation and socio-economic priorities (Hoggarth, *et al.*, 2006) including fishers information.

3.3.1 Catch per Unit Effort (CPUE)

While it is acknowledged that CPUE is derived from fishery removals as opposed to being directly related to the biology of the individual species being assessed, CPUE data have been used successfully as a proxy indicator of stock status in many fisheries (e.g. Breen, *et al.*, 2003; Tully, *et al.*, 2006; ICES, 2010a), and were a fairly consistent feature of the case studies presented by Miethe, *et al.* (2016). The shortcomings of such data have been previously discussed in Section 3.2.1.2 with respect to their use as an index of abundance in stock

assessment. The use of industry led data to develop CPUE trends can, similarly to abundance data, be significantly influenced by catchability (influenced by factors such as bait type, gear saturation, physiology), and interpretation can be challenging if there is not a good understanding of the relationship between CPUE and abundance. The calculation of effort for creel and pot fisheries can also be problematic where commercial species other than the target species are also caught and landed, this is particularly the case for lobsters which are often landed as a bycatch. Hilborn and Walters (1992) outline some issues that can arise in the use of CPUE as an index of stock abundance. These are that CPUE can remain high while stocks decline if there is aggregation of the target species and fisheries are efficient at locating the target stock. Also, CPUE can decline rapidly while the stock remains largely untouched if small concentrations are fished heavily. Maunder and Punt (2004) provide a review of standardisation methods which can be utilised to incorporate fisheries dependent data into the stock assessment process. The use of CPUE can be also be enhanced if interpretation is carried out in conjunction with size based indicators (Miethe, *et al.*, 2016) and in this fisher led data collection could provide added value to information gathered via logbook returns.

There are several suggested mechanisms for incorporating CPUE into a harvest control rule (Breen, 1993). These include comparing the observed CPUE against a target level; observations can be made on the rate of change in CPUE over two or more years, CPUE can also be used with a catchability co-efficient (q) to estimate population biomass; using two or more years of catch and estimated biomass calculations on current surplus production can be made.

Technical Appendix 4 explores the possibility that the daily landings logs from the lobster and crab fisheries could be used as an index of resource abundance. These results are limited to Shetland, where the unique availability of effort data makes it possible to assess whether trend information is lost when using daily catch instead of LPUE to, via GLM analyses, obtain an index of annual abundance. The analysis shown in Technical Appendix 4 suggest that this is not the case, that the use of daily catch information has potential value as an abundance index. An important objection to this conclusion is that there may be a systematic trend in the number of creels per vessel that would nullify the acceptability of such an approach. This objection was tested by running GLM analysis on the creels hauled per day per vessel. The results show very little or no overall trends in the number of creels over the last ten years, for Shetland. This result again highlights that there is likely resource abundance level information in the daily catch data. Whether this result is exportable to the other assessment areas is difficult to ascertain from the data and analyses presented here, principally because there are no or very few effort records from these other assessment areas. Prudence may well dictate the advisability of checking the GLM analyses for daily catches in other assessment areas, as a first and perhaps interim assessment of the validity of the equilibrium assumptions, and perhaps for other uses (such as running RY or surplus production models). The reasoning underlying this recommendation is of course somewhat circular. Some independent verification of trends in the number of creels pulled per day may however be accessible directly from fishers, and would represent a valuable application of fisher data. If such inputs cast doubt on whether vessels have used the same number of creel pulls per day, then one cannot proceed with the assumption of invariance in creels pulled per vessel per day, but by the same token then the equilibrium assumption underlying LCA cannot be upheld. Another factor which is relevant here is annual catch per se. If the equilibrium assumption underlying LCA is indeed

valid then one would expect to see considerable stability and absence of overall trend in catches over a time period of, say, the last ten years.

If some confidence in daily catches as a proxy for CPUE can be established, then it becomes possible to make use of surplus production models or replacement yield (RY) models for crab and lobster stocks, or perhaps dynamic length based stock assessment approaches which use a combination of CPUE and catch-at-length information. Consideration of which approach is most suitable is that surplus production and RY methods are perhaps best used in conjunction with TAC (Total Allowable Catch) or TAE (Total Allowable Effort) control regimes, which is presently not a feature of the crab and lobster stocks under consideration in this document, which use F based targets in their management. Dynamic length based stock assessment approaches on the other hand can be structured to produce outputs relevant to both F based and TAC/TAE based management.

3.3.2 Length based and biological indicators

The collection of length based data from crustacean fisheries through fisher led sampling programmes would have the benefit of providing the size distribution for the whole catch, rather than just the landed portion. This would provide data on mean size for both males and females and total catch sex ratio data; it would also have the potential to gather information on reproductive status e.g. proportion of berried females, size at maturity (from the smallest size of berried females) and timing of the moult through the presence of soft individuals. All of these factors would have the potential to be utilised as indicators in fisheries management. An example would be the Shetland velvet crab fishery where the mean size of males and the sex ratio are both used as reference points in a fishery where there are differential fishing rates between the sexes. Also in this fishery the proportion of soft individuals in the moult is utilised by fishers to initiate real time closures of the fishery to avoid the capture of soft individuals. This approach also has the benefit of being sensitive to the variability over local scales in the timing of the moult.

Miethe, *et al.* (2016) provide a comprehensive list of length-based indicators, and point out that decreases in the mean length and median length of the catch for example, can be useful in identifying the presence of high exploitation rates. Where there is variable recruitment in population, however, this can cause noise in the data and lessen usefulness of such indicators, though approaches are being taken to examine the potential for using truncated distributions to lessen sensitivity to recruitment (ICES, 2017). Generating a temporally and spatially detailed dataset from industry generated data could help to provide a better understanding of these changes and it may be that quartiles or set percentiles can be utilised to provide context for trends in the data which may result from biologically induced variability.

3.3.3 Spatial indicators

Miethe, *et al.* (2016) summarises the main spatial indicators for stocks (e.g. centre of gravity, occupancy, spreading area) and from fishery-dependent data (e.g. total catch per exploited area). The latter relies on good quality spatial information of fishing vessels and in the Scottish context would greatly benefit from much more detail than is currently available through the EU VMS system. It would also benefit from a complete coverage of the fishery (as discussed in later Sections, see Sections 4.1 and 5). It would then be possible to monitor the fishing footprint over time to quantify changes in fishing activity, this could be linked with stock data

from surveys. As pointed out in Miethe, et al (2016) it is important to take into account the socio-economic factors which may affect fisher behaviour, for example distance from port. This is also an important consideration when selecting vessels to participate in data collection.

Fishing data are currently reported by ICES square, and for vessels with an overall length of 12 m or less, a start position is also recorded (see Table 2.1 of Section 2.1.1). However, start positions will only be incorporated into the new COMPASS database once up and running. For larger vessels (greater than 12 m in length), a mandatory EU VMS system is also installed which reports the vessel details (e.g. vessel name, position, etc.) every two hours. This system was primarily designed for the larger demersal and pelagic vessels which generally fish for longer periods than, for example, an inshore scallop dredger. The accuracy of these VMS units have been shown to be poor, especially when a vessel is engaged in intricate fishing tows (e.g. performing multiple turns during one tow) as is common in many inshore shellfish fisheries (Skaar, et al., 2011). A more recent study has also demonstrated that the current VMS recording frequency of two hours is not suitable for all fishing types (Katara and Silva, 2017), for example two hourly pings would not provide effective spatial data for an inshore scallop fishery that could then be utilised in marine spatial planning.

The Scottish Government has stated in the Inshore Fisheries Strategy that “an appropriate form of vessel monitoring” shall be implemented, with the aim of proving “good quality information on the footprint of inshore fishing by 2020.” In order to develop effective spatial indices locational data for inshore fisheries should provide an accurate footprint of fishing activity, both spatially and temporally.

The use of data collection systems onboard vessels will have the advantage of being able to accurately attribute catch characteristics to a specific location, or for the data to be aggregated at whatever spatial scale is considered to be most suitable at the local management level. This means that spatial variability, an intrinsic characteristic of shellfish stocks, can be much better described within the context of the fishery. The advantage of this mode of data collection over surveys will be in the provision of a time series of data, as opposed to a snapshot, which could be influenced by reproductive behaviours, or changes in environmental characteristics.

3.3.4 Maximum Sustainable Yield (MSY)

The Scottish Inshore Fisheries Strategy makes specific reference to managing fisheries towards a target of MSY by 2020 as part of Marine Scotland’s obligations under the Marine Strategy Framework Directive (MSFD). The EU commission produced an advice document on the implementation of sustainability through Maximum Sustainable Yield (European Commission, 2006). This document states that plans to rebuild stocks should be carried out by managing fishing effort and not through attempts to manage biomass levels. It also states that “where, due to a lack of data or other circumstances, scientific advice cannot quantify the actions needed to reach maximum sustainable yield conditions, the plans should specify appropriate guidelines”. In this regard, proxies for MSY (which is difficult to define for shellfish fisheries) can be utilised in demonstrating that a fishery is being managed sustainably.

ICES describe B_{MSY} to be the spawning stock biomass corresponding to the maximum sustainable yield as defined by either an age structured assessment or from a production

model. As calculations of MSY are based on the outputs of these analytical models there needs to be a process by which the most appropriate model is selected and by which an acceptable reference point allocated based on the levels of uncertainty encountered. Reference points based on MSY do not necessarily perform well in this regard (Caddy and Mahon, 1995) and it is suggested that an accuracy rate of better than $\pm 20\%$ of effort yielding MSY would be unusual. ICES have produced advice on implementing an F_{msy} framework (ICES, 2010b) which advises that a broad range of metrics can be put forward to inform management (including CPUE), provided there is “some insight” into how indicators relate to stock abundance and/or exploitation, and that over time a functional series of metrics can be obtained.

Therefore, while MSY is the target set for fisheries, it may not be possible with the available data and stock assessment methods to provide an MSY based reference point for shellfish fisheries, and therefore a range of suitable proxy indicators should be developed.

3.3.5 Fishers' knowledge

It is important to acknowledge that fishers have a vast knowledge, understanding and experience of the stocks upon which they rely, and this information can be utilised in a meaningful way in the development of indicators (e.g. Macdonald, et al., 2014). The use of fishers' knowledge in a structured way can provide useful time series of data (Napier, 2014) which can be utilised as stand-alone indicators, or which can provide context to stock assessment outputs. The latter can be particularly important when fishers are observing current changes in their catch which have yet to be observed, recorded or interpreted via assessments.

4 POTENTIAL METHODOLOGIES FOR FISHER LED DATA COLLECTION

4.1 Fisher led data collection approaches

4.1.1 *Technology assisted data collection programmes*

In order to determine possible measures to enable fishers to carry out additional data collection to enhance the data available for stock assessment purposes, it is important to review what alternative approaches may be undertaken for the collection of fisheries data. This section summarises examples from Scotland and internationally which could inform a fisher led data collection approach to inform stock assessment for inshore fisheries. These examples are primarily linked to the use of technologies that are new in the context of Scottish inshore fisheries, and cover the following kinds of data that are relevant to and valuable for management:

- 1) Vessel location information
- 2) Discard information; number of discards, length of discards, sex of discards
- 3) Effort data
- 4) Environmental data
- 5) Length and sex information
- 6) Direct abundance/density estimates for crab and scallops on the sea bottom
- 7) Biological state information (soft shell)
- 8) Catch and effort

Within Scotland an investigation into some possible alternative data collection methodologies has been carried out which was a precursor of the SIFIDS project. The initial project titled “Evidence gathering in support of sustainable Scottish inshore fisheries”, a European Fisheries Fund (EFF) funded project, was a series of eight work packages designed to be pilot studies aiming to fill evidence gaps and trialling new technologies to support effective management of Scottish inshore fisheries. The project ended in 2015. James, *et al.* (2015) used an Automatic Identification System (AIS) to provide high frequency location data of inshore fishing vessels around Scotland. Course, *et al.* (2015) tested the use of on-board technology for catch and effort information. The authors looked at an electronic monitoring system to obtain information on catch, effort, and fishing location by using three cameras showing an overall view of the vessel, a view of the catch, and view of the discards (Table 4.1). Data storage tags and Radio Frequency Identification (RFID) tags were trialled for effort and environmental data. The use of Bluetooth electronic calipers with an integrated button for sexing the animal were trialled for fisher self-sampling of the retained catch. An automated discard chute was created using three additional cameras to obtain information on the number, sex ratio, and length of discards. All the information from the electronic monitoring system, including video images, was stored on a hard drive aboard the vessel and, at a later date, the hard drive was removed so the data could be analysed back on land. The authors were then able to compare information from fishers self-sampling, on-board samplers, and video analysis. The authors suggest using 50 to 100 inshore vessels equipped with electronic monitoring technology to cover the west coast of Scotland but it is unclear from the report what the justification was for choosing this number of vessels. The report also suggested fisher self-sampling would not provide accurate data in the long-term due to sampling fatigue, if the fisher was to provide extra data and extra samples on top of their daily job of fishing. Out of

568 fishing trips from 11 vessels (range of 16 to 82 fishing trips per vessel), the EM technology used was found to be robust without any break downs and was considered to be a reliable source of information.

Towed camera surveys have been used as a tool for determining abundance in the sea scallop, *Placopecten magellanicus*, (Stokesbury, 2002; Stokesbury, *et al.*, 2004; Adams, *et al.*, 2010) and the king, *Pecten maximus*, and queen, *Aequipecten opercularis*, scallops (Lambert, *et al.*, 2012). Towed video surveys were found to be an effective tool in determining sea scallop abundance in the mid-Atlantic and Georges Bank (Stokesbury, 2002; Stokesbury, *et al.*, 2004). The authors found the survey to be “fast, accurate, and precise” as well as providing biological and habitat information for the scallops. However, this species tend to remain on top of the sediment, rather than partly buried as seen in the local king scallop species. Lambert, *et al.* (2012) assessed the use of video and still images in determining scallop (king and queen scallops) abundance compared with the more traditional dredge survey design for Welsh waters. The authors found consistent and reliable results for queen scallops but did not find the technique useful for king scallops. It was more difficult to see king scallops from the video and still images due to them being partly buried in the sediment. The authors also noted that certain sediment types (e.g. sand) were easier to spot scallops, compared with more heterogeneous sediments (e.g. rocks with epifaunal growth).

A camera system mounted on a towed sledge has been used in the snow crab (*Chionoecetes opilio*) fishery in North America (Conan and Maynard, 1987). The camera sledge was fitted with a front rake which dug into the sediment, effectively flipping semi-buried crabs into the camera’s field of view. These are then counted either on board the vessel or through the recorded video feed at a later date. Within the snow crab fishery in Atlantic Canada, the percentage of soft shelled crabs is taken into account with shorter fishing seasons and closed areas (Addison, *et al.*, 2013). Effective monitoring of soft shell crabs is carried out by at-sea observers. Research on the velvet crab (*Necora puber*) fishery in Shetland highlighted the potential for real time closures based on the proportion of soft crabs being caught (Leslie and Shelmerdine, 2008). Fishers monitor the levels of soft crab within their catch and then register an eight week closed period, this allows the management system to be reactive to the small scale variability often seen in shellfish species.

In the United States, five of their fisheries have implemented an electronic monitoring (EM) program¹³. Fishing types covered by electronic monitoring include longlines, midwater trawling, bottom trawling, fixed gear, and pots. In order to address the different monitoring requirements from each region and fishery, each region published a “regional electronic technology implementation plan” which helped to identify promising technologies to be incorporated into each fishery. Within the Alaska region, some of the technologies already in operation include electronic recording for logbooks and observer data, calibrated flow scales, VMS, and video, although not all technology was used in all fisheries. Video was highlighted for potential EM application as a tool for catch estimation, monitoring deck sorting, and compliance monitoring. Electronic monitoring does not cover all fisheries and the National Oceanic and Atmospheric Administration (NOAA) have identified several hurdles in implementing EM technology within a fishery. Some of these hurdles included “handling of the enormous amount of data generated by electronic monitoring, effects on time series of

¹³ See www.fisheries.noaa.gov/national/fisheries-observers/electronic-monitoring

data used in stock assessments, confidentiality, and cost allocation between government and non-government partners” as well as physical factors such as varied boat designs and sizes, low light, and cost implications.

A Voice Data Recording System (VDRS) has been successfully used in Michigan, USA, since 2009 as a way of increasing efficiency and accuracy when collecting biological data and, since 2015, a mobile version of the VDRS has been used aboard commercial vessels (Sitar and Traynor, 2017). The mobile VDRS setup included a tablet/laptop, wireless headset microphone, and digital voice recorder with the option to integrate other devices (e.g. a tag reader). The authors found that the VDRS system reduced the amount of collecting and processing steps from seven to four, was more efficient and less prone to errors when compared to the traditional way of collecting and processing data. They also noted substantial savings in both cost and time.

Electronic monitoring is compulsory in the Australian commercial fishery for Tuna and Billfish, and the gillnet hook and trap fishery¹⁴. The EM system uses a combination of video cameras and fishing activity sensors such as hydraulic and drum-rotation sensors. The information is used in management and by scientists for producing stock assessments.

Electronic mechanisms for the collection and processing of data can greatly enhance efficiency, however, compromises over data quality may result from this. Any risk associated with data collection and data quality must be effectively quantified and communicated to fisheries managers.

¹⁴ See www.afma.gov.au/monitoring-enforcement/electronic-monitoring-program/

Table 4.1 Summary of main findings of the different crustacean sampling techniques used during the work reported on by Course, et al. (2015).

Sampling technique	Measurements taken	Comments on measurements
Fisher self-sampling	Retained counts Retained weights Discarded counts Discarded weights Sex ratios Effort data	Retained catch data was generally good. Estimated. Discard data usually supplied for target species but not for bycatch of other species. Weights were estimated and not considered reliable. Sex ratios, in most cases, were best guesses as an estimated percentage for discarded and retained. Number of strings data was good but creel number did not always take into account lost gear.
		Main highlighted issue of self-sampling was “longevity of good performance” for the fisher to provide extra data and extra sampling.
Electronic Monitoring (EM) system	Retained counts Retained weights Discarded counts Discarded weights Sex ratios Effort data	In most cases, counts were easy to achieve, but not when the fisher emptied the whole creel at once. Very unreliable from video footage. Counts had to be multiplied up from mean individual weights. In most cases, counts were easy to achieve, but not when the fisher emptied the whole creel at once. Scallop fisher lined discards up on rail prior to discarding, making counts easy. Very unreliable from video footage. Counts had to be multiplied up from mean individual weights. Easy to obtain during banding or nicking of claws, although nicking does not happen on all vessels. Can easily link catch data with effort and a fishing position. However, when strings were close together, effort was hard to distinguish.
		EM analysis did not always match up with what the fisher had reported, especially for effort and discards.

Sampling technique	Measurements taken	Comments on measurements
RFID tags	Creel number	Accurate effort data but would need one tag per creel.
	Soak time	Calculated from when the tag was swiped at the shooting reader to when the tag was swiped at the hauling reader.
	Position	Position was recorded at hauling.
		Problems with readers reading the tags after a while, possibly due to damage or sea water effects.
Weighing catch at sea	Weight	Safety issues and practicalities of sea trials prohibited any data collection.
Data Storage Tag (DST)	Temperature	Measures temperature and pressure every 5 minutes.
	Pressure	Pressure can be used to calculate soak time
		Potential application for other science disciplines (e.g. oceanography) but does not address potential data ownership issues.
Discard chute	Counts	Provided good counts for crabs and lobsters.
	Length	Not good at measuring animals.
	Sex	Could sex some crabs but poor with lobsters.
Bluetooth digital callipers	Length	Authors suggested a fisher self-sample for 10 minutes every trip on one or two species to gather data [this equates to 96.6 measurements/10 minutes]. However, they experienced duplicate recordings and 6% of the data had errors.
	Sex	

4.1.2 Sentinel vessels for the collection of biological data

The institute of Marine Research in Norway uses a Reference Fleet to obtain biological and fisheries data from the commercial fishing fleet (Williams, 2016). The reference fleet consists of a High Seas Fleet and a Coastal Fleet. The vessels are chartered to participate in data collection and supply information on total catch, including bycatch species and those which are exempt and non-exempt from the discards ban. Data are collected on age and length for fish species. The total budget for the reference fleet in 2015 was 24.5 million NOK (around £2.5 million). In addition to routine data collection, the reference fleet are also asked to participate in data collection for other research institutes and for other types of data (e.g. oceanographic and environmental data). The high seas reference fleet is able to take advantage of technological advancements through the use of electronic measuring boards, but the large size of these mean that they are unsuitable for the coastal reference fleet. For these smaller vessels rugged tablets have been developed with an associated fish measuring app, but it is acknowledged that not all fishers will want to use this with some preferring to use paper and pencil to record their data (Williams, 2016). The data are mainly used for assessment purposes such as estimating total catch by length/age group, which is then used to improve on the stock assessments and fisheries management. However, one of the main concerns of the program is that there are “*too few vessels to cover the complexity and size of the Norwegian fishing fleet*”.

The Canadian Government have implemented a series of sentinel fisheries projects along their Atlantic coast in order to gain information on cod stocks in the area (see Gillis, 2002 for an overview). The cod fishery in the northwest Atlantic closed during the 1990s due to a collapse in the stocks. Concerns were raised on how the closures would impact any stock assessment process and in mid-1994, government funding was made available to carry out organised and controlled harvesting through commercial fishers. Since 1996, initial government funding allocations for the sentinel program were \$6 000 000 (around £4.6 million); in 2000, this figure was just over \$7 000 000 (around £5.4 million). In 2001 there were 27 distinct sentinel projects spread over five regions. Projects varied between and within regions but included “*stratified random surveys, controlled fishing for index purposes, and commercial index fisheries as well as a number of more specialised project designs*.” (Gillis, 2002). Data from the sentinel programs also provided information on other species, other than the targeted cod stocks, and included various gear types. Only vessels with historical experience in the commercial fishery were eligible to take part in the sentinel programs. Those selected were required to take part in a six week course which covered “*scientific sampling methods and equipment, computer use, resource assessment basics, and presentation skills*” (Parsons and Stead, 2009). Fishing locations were initially identified through consultation with harvesters to ensure good representation of cod fishing grounds and geographical coverage. Mobile gear was standardised on all vessels through a restrictor cable and a standard was established for fixed gears (Chouinard, et al., 1999).

Ireland operate a Celtic Sea herring sentinel management fishery for small vessels (<17 m overall length) using trawls or seines¹⁵. The sentinel fishery operates within the Dunmore Box, an important area for herring reproduction which is closed to the main fishery. By allowing a

¹⁵ See www.agriculture.gov.ie/seafood/seafoodpolicy/forms/cecticseaherringsentinelmanagement

small fishery (sentinel fishery), managers would be able to monitor the state of the overall herring stock in the area¹⁶. Vessels are required to book in to the fishery by a specified date in order to receive their weekly quota.

Selecting vessels to make up a representative reference fleet, or sentinel vessel sampling programme, will require a range of information. A good understanding of the fleet structure and fishing practices is key to understanding which vessels will be able to participate in sampling. For example an older vessel with limited deck space would not be appropriate for a complex electronic data collection solution; and while larger nomadic vessels may be suitable to host a range of equipment, their fishing practices (spatial and seasonal distribution) may produce data which is not representative of the wider fleet, or which may require additional processing prior to inclusion in a stock assessment. With the present level of available data (summarised here in Section 1.2), it would not be possible to determine which vessels would be appropriate for a sentinel fleet without engaging with local fisheries associations in the first instance. When selecting vessels, both operational and statistical factors should be considered. Operational factors would include elements such as:

- history of involvement in scientific sampling studies,
- willingness of the crew to participate in self-sampling programmes,
- space for an observer on the vessel (should this be required),
- vessel safety considerations,
- the scale of the vessel's fishing operations for species of interest,
- consistency of the vessel's operations from year to year,
- likely future participation of the vessel in the fishery.

The set of vessels to be chosen for sampling should be vessels whose fishing activities represent all fisheries management areas of interest, and the major strata of such fisheries within management areas. The number of vessels and their likely fishing activities should be chosen to minimise insofar as possible, the coefficient of variation of the relevant estimates which are the subject of the sampling programme. The estimates of interest in the case of the crab, lobster and scallop fisheries considered here include, for example:

- A variety of biological measurements such as weight – length, maturity stage, other life history stages, gender.
- An annual estimate of catch-at-age, only relevant to scallops
- An annual index of CPUE based on catch and effort data, relevant to scallops, crab or lobster
- An annual measure of catch-at-length, relevant to scallops, crab or lobster

The C.V. for CPUE, catch-at-age, or catch-at-length must be sufficiently small so that the resultant changes in quantities of relevance to management (such management quantities would frequently be produced via stock assessments) are discernible, either from one year to the next, or over a defined period of time of five or 10 years. The number of vessels that should be included in data collection for producing an index of, say, mean size, and the frequency with which such sampling is conducted on those vessels, will depend on, amongst other factors, the scale of the so-called “vessel effect” (in other words how the value of the index is affected by the vessel chosen for sampling, other things being equal). Overall the success of any sentinel vessel programme will be affected by three main factors:

¹⁶ See www.kildarestreet.com/wrans/?id=2016-01-13a.1046

- Stakeholder buy-in
- Payment programmes
- Effective scheme administration

When considering a Scottish reference fleet, it is important to better understand how the shellfish fleet is made up between and within each region. Gaining a better understanding of the distribution of gear type (Figure 4.1), vessel size (Figure 4.2), and vessel age (Figure 4.3) would be a good starting point when considering any potential reference fleet but should also be considered in combination with the already mentioned methods above. Creels were the dominant gear type for all five regions (Figure 4.1) which were also dominated by vessels smaller than 10 m in overall length (Figure 4.2). However, the physical attributes of each regional shellfish fleet showed distinct variation in gear type, length, and age. The second most frequent gear type for both Shetland and the West Coast was dredging (the other three regions had high numbers of “*Nephrops*” and “Other” gear types, Figure 4.1). However, dredgers in Shetland were found to be much smaller than those in the West Coast RIFG (the latter region containing 41 vessels greater than 15 m compared with one vessel of this size class in Shetland). This was reflected in the breakdown of lengths between regions, which, with the exception of West Coast, was found to decrease with increasing vessel size. Although mean age remained relatively constant between regions, ranging from a mean of 1985 in Orkney to 1992 in North and East Coast, all regions, apart from Shetland, had vessels which were built prior to 1940 and all regions had vessels built later than 2010. A similar pattern was noted for creel vessels in each region but vessels with dredge and *Nephrops* gear showed much greater variation in age composition (means and ranges, see Figure 4.3).

Older vessels may not have the capacity to run multiple computer systems and vessels which seem to be of a suitable overall size on paper may not be a practical option due to, for example, a small or over crowded wheelhouse potentially prohibiting the installation of extra computer equipment; or limited room on deck to install equipment or safely accommodate an observer with their equipment. Such considerations would have to be assessed on a vessel-by-vessel basis through vessel visits and regular communication with potential skippers.

It would also be important to better understand the fishing practices of each vessel within any potential reference fleet. Variation within the Scottish shellfish fishery is well known and includes:

- Seasonal variation, where scallop dredgers switch from dredging scallops to fishing for squid or finfish species.
- Market-driven variation, where fishers switch target species due to market demand (e.g. an increase in catching/storing of lobsters in the lead up to Christmas).
- Temporal variation in catch composition, where vessels alter their target species effort from, for example, brown crabs to velvet crabs.

It may also be important to understand what proportion of the local fleet is made up of full time fishers and what proportion of fishers have other employment commitments which reduce their fishing capacity.

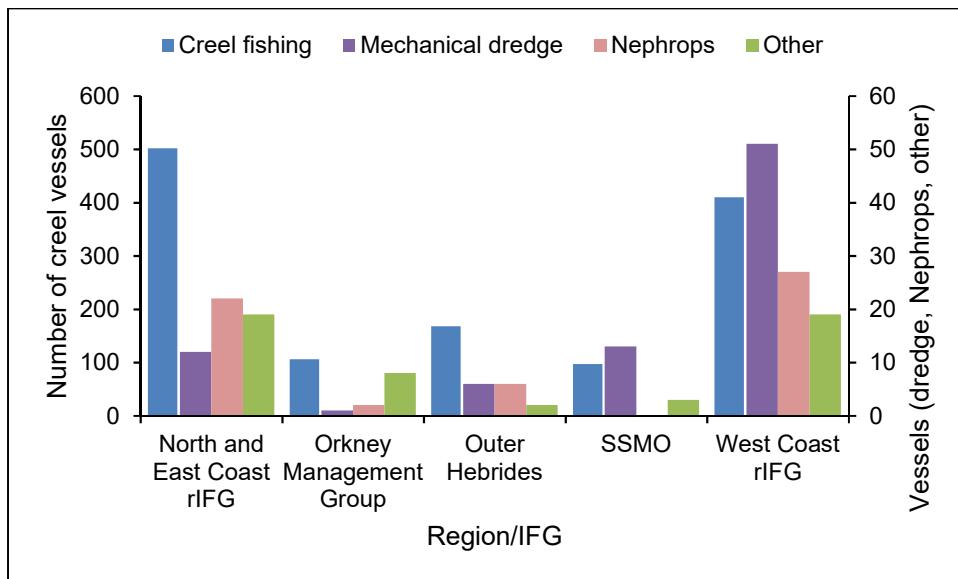


Figure 4.1 Number of vessels per gear type for each RIFG. Mechanical dredge (purple), Nephrops (pink), and Other (green) gear types are represented on the secondary y-axis with Creel fishing (blue) on the primary y-axis. Data obtained from Marine Scotland on request.

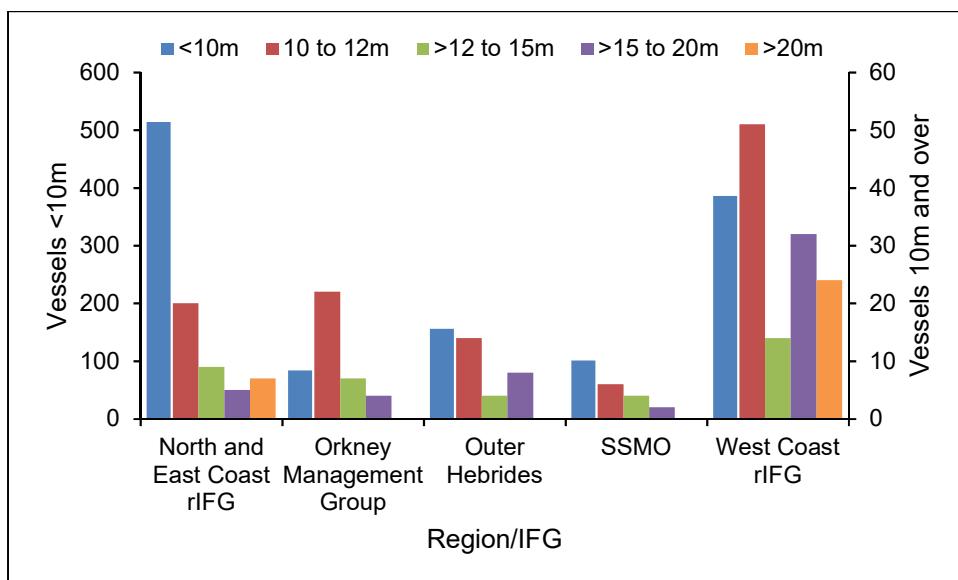


Figure 4.2 Number of vessels per overall length class for each RIFG. Vessels under 10 m (blue) are represented on the primary y-axis and all other vessel sizes are represented on the secondary y-axis. Data obtained from Marine Scotland by request.

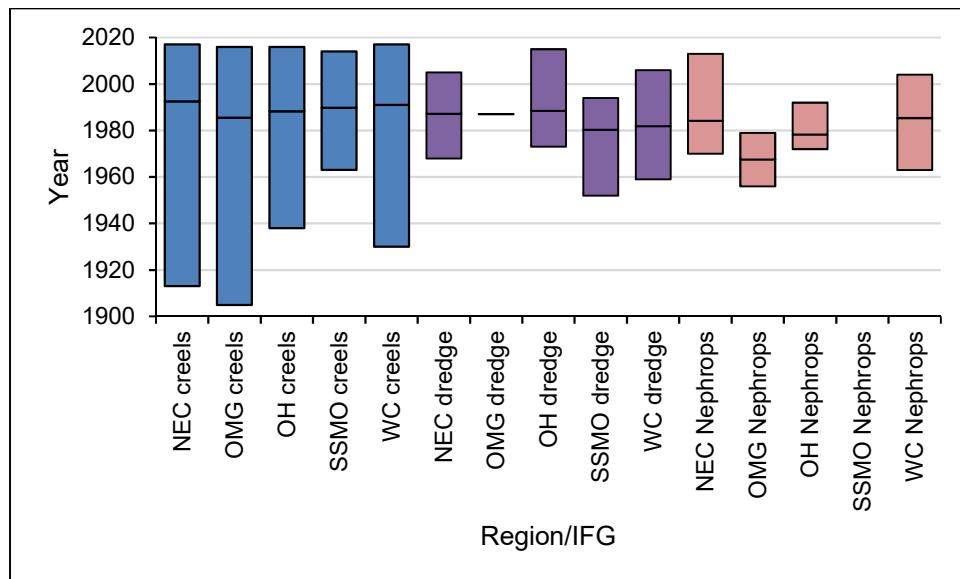


Figure 4.3 Age range and mean age of vessels operating creels (blue), dredges (purple), and *Nephrops* (pink) gear in the five RIFG areas of North and East Coast (NEC), Orkney Management Group (OMG), Outer Hebrides (OH), SSMO, and West Coast (WC). Data obtained from Marine Scotland by request.

4.1.3 Self-sampling programmes

As a different approach to the use of sentinel vessels, self-sampling programmes exist in many fisheries. An example is the South African South Coast rock lobster fishery for which a self-sampling programme was introduced in 2006, and in which all vessels participate. Data form logsheets have been used in the self-sampling programme (Figure 4.4), although some vessels have adopted the use of an electronic logbook system to aid in data collection. In this long-line pot fishery the self-sampling programme involves sampling a limited number of lobsters per set. This programme is almost ten years old now and provides valuable length structure and sex information which is used in stock assessments, replacing a government funded observer programme which had previously provided the same data. The observer programme has been terminated due to insufficient government funds. A common concern is that the data from self-sampling programmes are not necessarily reliable. This was an issue with the self-sampling programme in the South Coast rock lobster fishery and so it was necessary to “ground truth” the self-sampling data by comparison with data collected at the same time (for overlapping years) in the now defunct scientific observer programme. There are many other ways that data from a self-sampling programme can be validated, including for example occasional and random audits.

Fisher self-sampling for scallops has also been carried out under the CEFAS Red bag scheme which was launched in 2011 as a means of obtaining sufficient biological information regarding scallop stocks with which to run stock assessments (Bell, *et al.*, 2014). Scallop vessels signing up to the scheme were required to retain a sample of the catch, representing all scallops above the MLS from two or three dredges ($n = 120$ minimum), in red bags marked with details of the catch. These scallops would be landed as usual to the processors who would retain the flat shells for Cefas to collect and process. This method allows for relatively little disruption to normal fishing practice and no loss in earnings to either the fisher or processor. Seven sampling areas were defined on the basis of knowledge regarding fisheries and biology:

- 1) North Sea (ICES area IV)
- 2) Eastern Channel (ICES area VIId)
- 3) Lyme Bay (East VIIe to Start Point, from coastline down to 49°30'N)
- 4) VIIe west of Start Point from coastline down to 49°30'N
- 5) Offshore (anything south of 49°30'N in VIIe and VIIh)
- 6) Celtic Sea (VIIg and VIIf)
- 7) Irish Sea (VIIa)

Quarterly sampling targets were set (six samples per area per quarter) but these were rarely met. Sampling was, to an extent, opportunistic the opportunity for obtaining samples was linked to the level of fishing activity. A total of 60 vessels contributed to the 150 samples collected between the fourth quarter of 2011 and the second quarter of 2014. Of these vessels, six contributed over 50% of the samples and many were the smaller (<15 m) vessels. These data were collected in the absence of a wider stock assessment programme and did not generate sufficient data to provide robust statements on stock biomass or exploitation rates. The data collected did however, allow a preliminary investigation into the potential exploitation rates for two of the seven areas studied. It should be noted that the data volumes were limited and potentially biased by the restricted spatial coverage. This meant that the data was not necessarily reflective of the wider stocks, partly due to the number of participating vessels and partly due to the restrictions placed on the fishery by the Western Waters regime. Targeted work would be required to estimate the realised magnitude of potential biases in the data. Practical issues highlighted as part of this work were the engagement and continued participation of fishers in the study, and the administrative burden of sample collection, which took a considerable amount of effort. Some samples were also lacking in sufficient catch data from the fishers.

a)

EXTENDED LOG SHEETS FOR SOUTH COAST ROCK LOBSTER

Trip Sheet	Note: One sheet to be filled out for each Trip				
Vessel Details					
Vessel Owning Company					
Vessel Name					
Vessel Registration No.					
Skipper Name					
Rights Holders	Permit No.				
(To be completed at office)		(To be completed at office)			
Trip Details					
HH/MM		DD/MM/YY			
Start Time		Departure Date			
End Time		Arrival Date			
Departure Port		Landing Port			
Total No. of Days in trip		No. of Fishing Days			
No. of Non-Fishing Days		Reason			
		Reason			
		Reason			
Trip Catch Data (i.e. summary for the whole Trip)					
Name of Rights Holder	Weight (Kg) Whole Live	Weight (Kg) Tails	Weight (Kg) By-Catch	Total Green Weight (kg) Equal to the sum of live hold and converted tails weight	Other (Kg)

pg 1

b)

Fishing Day Information		Set No.		Fishing Day No.			
Position Information		Note: To be filled out for each day					
Date DD-MM-YY	Time HH/MM	Position DD-MM	Grid No. DD-MM	Grid No.	Depth(m)		
Grid Start		Lat.	Long.				
Grid End		Lat.	Long.				
Gear Information							
No. of traps set	No. of traps hauled	Avg. No. traps/trap	Seak. (hrs)	Line Lengths anchor to anchor(m)	Bait type		
					Rate per Trap(kg)		
					No. of Traps Hauled		
					No. of traps lost		
Environmental Data							
Wind (knots)	Air Temp (°C)	Surface Sea Temp (°C)	Wave Height (m)	Surface Current (knots)	Bottom Current (knots)	Bubbles Temp (°C)	
Cloud Cover	Sea Cond. (breakfast scale)	Wind Direction		Surface Current Direction		Bottom Current Direction	
<input type="checkbox"/> 0	<input type="checkbox"/> 1	NW	N	NE	E	NE	
<input type="checkbox"/> 1/8	<input type="checkbox"/> 2	WNW	WN	ENE	EN	ENE	
<input type="checkbox"/> 2/8	<input type="checkbox"/> 3	WWN	W	NE	E	NE	
<input type="checkbox"/> 3/8	<input type="checkbox"/> 4	WW	W	ENE	EN	ENE	
<input type="checkbox"/> 4/8	<input type="checkbox"/> 5	WSW	SW	SE	SE	SE	
<input type="checkbox"/> 5/8	<input type="checkbox"/> 6	WS	S	SS	SE	SE	
<input type="checkbox"/> 6/8	<input type="checkbox"/> 7	WSW	SW	SE	SE	SE	
<input type="checkbox"/> 7/8	<input type="checkbox"/> 8	SW	S	SE	SE	SE	
<input type="checkbox"/> 8/8	<input type="checkbox"/> 9	SW	S	SE	SE	SE	
<input type="checkbox"/> 9/8	<input type="checkbox"/> 10	SW	S	SE	SE	SE	
<input type="checkbox"/> 10/8	<input type="checkbox"/> 11	SW	S	SE	SE	SE	
<input type="checkbox"/> 11/8	<input type="checkbox"/> 12	SW	S	SE	SE	SE	
		Bottom Type		<input type="checkbox"/> rock	<input type="checkbox"/> mud	<input type="checkbox"/> sand	<input type="checkbox"/> mix* *specify:
Daily Catch Data						Estimated capacity of carton (kg)	
Number of Lobsters	Weight Live (kg)		Number of cartons of frozen tails				
Daily By-Catch Data						Approximate capacity of each bag (kg)	
Species (e.g. Octopus)	Weight (kg)	Estimated Number	Number of Bags				
Tagged Lobster							
Tag colour	Tag no.	Date DD-MM-YY	Latitude DD-MM	Longitude DD-MM	Carcass Length (mm)	Sex M F	
						<input type="checkbox"/> <input type="checkbox"/>	
						<input type="checkbox"/> <input type="checkbox"/>	
						<input type="checkbox"/> <input type="checkbox"/>	

pg 2

Note: M=Male, F=Female, S=Spawning

Figure 4.4 Extended logsheets used as part of the self-sampling programme in the South Coast rock lobster fishery in South Africa.

4.1.4 Mark recapture

There are several relevant examples of mark recapture projects for shellfish in Scotland, mainly focusing on brown crab (though some small scale work on lobsters and scallops have been carried out). Marine Scotland Science carried out tagging programme using charter vessels at stations to the north and west of Orkney (Jones, et al., 2010). This work utilised T-bar tags which can be retained following the moult and can therefore be utilised to gather data on growth rates, which is very useful for refining stock assessment models (particularly if there are local variations growth). The downside of such a technique is that tagging involves piercing the carapace of the individual which can result in increased post tagging mortality rates and is generally carried out by suitably trained scientific staff, rather than fishers themselves. The MSS study reported that 76% of tagged crabs survived the tagging process in aquarium studies, but of the five observed individuals which moulted only two retained their tags. The tag return rate was quite low in this study at 1.3%, which could be a result of the large study area or perhaps a lack of tag retention. It is possible that the crab's behavioural utilisation of rock crevices could cause wear to T-bar type tags. Useful information on stock distributions and potentially abundance can also be gained by external tagging techniques, as used in local studies in Orkney (Coleman and Rodrigues, 2017) and Shetland (unpublished). These tags placed on the claw have the advantage of being non-invasive and easy to fit, which make them suitable for fishers to administer to crabs.

The study implemented in Orkney (Coleman and Rodrigues, 2017) was carried out to provide information on the status of the crab stock in order to inform sustainable fisheries management; and also to provide spatial data on crab biology, fisheries and habitat for use in the context of the marine renewables industry. The work focussed on fishers or observers tagging "white crabs" which have recently moulted, and therefore have no economic value. At the time of tagging the size, sex, and reproductive status of female crabs were recorded. This study recorded a higher recapture rate than the work of MSS (Jones, et al., 2010), and both studies reported significant movements of individuals between inshore and offshore areas. These crab movements suggest that there is connectivity between inshore and offshore stocks and between populations in the north of Scotland and to the west. The studies also identified areas where crabs congregate and suggest these could be important for reproduction. More work is required to further inform stock status and to identify habitats or areas, and further tagging over all of the RIFG areas is due to start in 2018. This work can clearly contribute to both stock assessment and to the development of effective fisheries management measures and there is considerable potential for fisher contribution to the data collection. There is a clear trade-off between the more invasive tagging methods which would provide growth data, and external tagging which can be more effectively implemented by fishers, and yield a greater volume of data.

Effective design of mark recapture studies is essential in order that the information gathered is fit for purpose. An understanding of the underlying biology of the species (catchability, moult cycle, reproductive behaviour etc.) will be critical to the interpretation of the data. The effective collection of such data at the local level can provide regionally specific input parameters for use in stock assessment.

5 SAMPLING OPTIMISATION

When considering the collection of additional data for inclusion in stock assessment there is a necessary trade-off between collecting sufficient quantities of high quality data, and the cost, both in terms of resource and finance, of doing so. Data for inclusion within stock assessment and management can include fisheries dependent data from fisheries observers, market sampling etc., and fisheries independent data which largely comes from surveys or research projects. Fisheries dependent data, while less costly to obtain, is affected by fisher's behaviour and requires a greater level of interpretation, as opposed to fisheries independent data which has the added advantage of considered survey design, in order to remove any potential biases in data collection, and therefore being more representative of the population being assessed. There is an inevitable balance between the relatively low cost which can be attributed to fisheries dependent data, and the comparatively higher costs of fisheries independent data collection which can often involve significant quantities of vessel time.

Industry led data collection has the potential to provide a cost effective mechanism by which additional fisheries dependent data can be collected, thereby providing a larger and more detailed data set. Surveys are necessarily restricted by cost, typically being carried out on an annual basis generally at a similar time of year and, in the case of the Scottish Scallop survey carried out on fixed stations; alternatively; a fisher led data collection system, while subject to the influence of fisher behaviour and changes in catchability, can provide an effective time series of data which can highlight within year variability as well as changes or trends between years.

In optimising data collection spending sufficient time on planning and design of any sampling protocol is essential to ensure that data are fit for purpose. Mackinson, *et al.* (2017) provide a detailed description of the components required to construct a programme with industry participation in data collection. They comprehensively detail the technical and practical considerations from identifying the specific issue, through design, primary considerations (e.g. location, resources, technical scope, data requirements), secondary considerations (e.g. number of vessels, trips to be sampled, technology, experience of fishers, data access and ownership), and tertiary considerations (e.g. availability of suitable vessels, protocols, data standards).

This section explores potential data collection based on the analyses carried out and also with regards to possible management aspirations.

5.1 Biological Data Collection

Sampling of biological data by Marine Scotland Science is carried out 15 sampling strata plus Shetland (see Section 2.1.2) of varying sampling frequency for each strata. A total of 73 sampling visits for the whole year covered all strata, except Shetland which is sampled separately under a MoU with NAFC Marine Centre, with each sampling visit consisting of one person. This equates to 173 person days to complete the biological sampling per year covering all 15 strata (calculated by the number of trips per year for each strata multiplied by the number of nights per sampling visit listed in Table 2.2). Without information on the vessel ID, which links sampling data to individual trips, it was not possible to relate the person sampling days to a number of trips sampled.

An examination of the length frequency data held for brown crab and lobster have shown that a reduction in the error variance associated with the data can be obtained by an increase in the sample size per trip, i.e. the number of individuals measured from a vessel on a particular day. This effect is true only up to a certain point when it then becomes necessary to increase the number of trips sampled. When examining the data for each assessment area and determining whether or not improvements could be made (Section 3.1.3) it can be seen that where additional sampling was highlighted an increase in the number of trips sampled was required, rather than an increase in the numbers of individuals sampled per trip. The majority of areas were being sampled sufficiently and for those areas where there is a requirement to increase the sample size, the increase is relatively modest. It is possible that a reduction in sampling effort in some areas where oversampling was occurring could free up resources for the additional trips required elsewhere, or additional sampling using a fisher led approach could be applied. Areas to be prioritised for additional sampling (based on data from 2016) are; the Clyde (lobsters, crabs, and scallops), North Coast (lobsters), South Minch (crabs), Ullapool (crabs), Orkney (Scallops).

The relatively modest increases in sampling recommended alongside the existing data collection carried out by Marine Scotland Science is a cost effective method of enhancing the current stock assessment programme, and acquiring additional data which could be utilised in fisheries management decision making. It is noted that the costs of collecting the length frequency data are not prohibitive (MSS pers. comm.), however Jardim, *et al.* (2015) report that there can be intrinsic costs associated with determination of the quality of the data and in providing resources to process information. It was noted by Marine Scotland Science that the design of the sampling programme was being reviewed (Pers. Comm.). There is potential to use the results presented here in that review.

When considering the deployment of new sampling equipment (e.g. video technology) to increase sample sizes, or when engaging fishers for self-sampling, it is necessary to establish an appropriate balance between cost and the number of vessels required to achieve statistical objectives (e.g. MWCV). In this study it was not possible to combine landings data with biological sampling data as we did not have access to vessel ID data. This made it impossible to calculate the component of the variance in length frequency estimates due to vessel. Given the likely installation of new sampling equipment on a select number of vessels (sentinel vessels), it is important to establish the minimum number of vessels that are required per stock assessment area, at the same time ensuring that a high proportion (or all) of the catch is sampled. It is recommended that a range of vessels be sampled and it is noted that it is more important that an appropriate vessel selection procedure be implemented, rather than simply increasing the number of vessels.

Those trips which produce data with a low sample size per trip and hence a large variance could be

- a) smaller vessels with short trips and low catches in general, or
- b) trips in which, simply vicariously, a given species is caught at a low proportion and the sample contains a low number of animals of this species.

In order to correct this problem, if (a) then it is necessary to target vessels which are larger or which can demonstrate consistent catches which permit a suitable sample size in every trip which is sampled, while if (b) then measures must be put in place to over sample species

which are present at a low proportion in a trip's catch, and hence in the random sample that is drawn. An investigation is required to determine the role of (a) and (b) before fixing on an approach going forwards.

The reference fleet should also comprise vessels that fish a greater number of statistical areas, and that fish year round, or fish throughout the fishing season. A potential approach could be based on landings from the last five years, and for each vessel in the dataset the following would be calculated:

- Average catch per trip: C
- Number of statistical areas fished per year: Ns
- Number of months fished per year: Nm

For each assessment area all vessels for which C is less than the median would be eliminated, to remove vessels for which the sample size is likely to be low. A calculation of Ns + Nm for each vessel would then permit vessels to be ranked in order of suitability.

This pragmatic approach to data collection would involve the identification of a relatively small number of willing, and practically suitable, vessels from each RIFG area to have equipment placed on board on a permanent basis therefore providing a baseline of data. This would have a clear benefit should electronic equipment be utilised in the collection of biological data, in that the number of units required within each assessment area would be relatively small, but could potentially be installed on a permanent/long term basis. These vessels would also, assuming effective sampling design, be able to provide a greater level of detail with regards to spatial and temporal variation in the biological data collected, which could be utilised in standardisation of the outputs. In order to increase efficiency in data processing and analysis a random sampling approach could be designed to sub sample the data from each vessel in the sentinel fleet.

The quality of fisher sampled data and costs of any additional processing should also be considered. In addition to the possible influences of fisher behaviour and catchability, bias can result from operational factors, such as how the catch is handled and sorted. Regular training of both skippers and crew will be required to ensure the quality of data collected. This training should be undertaken on-board the vessel so that any practical constraints can be identified and resolved (Mackinson, *et al.*, 2017). It is also useful to communicate effectively how the data will be used, and any potential pitfalls which can occur if shortcuts in data collection are taken. In this way the fishers collecting the data will understand the value of consistent data collection and why the combination of several different data types may be essential to the information being useable (e.g. length frequency data may need to be accurately matched with the spatial and temporal details of the trip).

There are potential cost benefits to providing additional data to enhance the existing stock assessment programmes; they can make use of existing data, including data management and assessment processes; there is added value in combining data streams; potentially fewer sentinel vessels/remote sampling equipment set ups need to be used. However, where there are any inherent difficulties within the system these will continue, for example; difficulties in accessing the data, spatial scale of reporting, frequency of assessments, and this may devalue the additional data collection. Conversely stand-alone data collection programmes can be designed to reduce these issues, with more effective data sharing and greater tailoring of data

collection and reporting programmes. This type of approach however, may require additional vessels to be sampled in order to produce a significantly robust data set, additional infrastructure may be required to support a greater access to data and more frequent reporting, and therefore greater costs may be incurred.

5.2 Spatial Data

With regards to spatial data, again the purpose of the data collection will be key to informing the level of data collection. There is a clear commitment to a suitable level of vessel monitoring within the Inshore Fisheries Strategy, which is linked to stock assessment through aspirations that the fishery be prosecuted at MSY. For this purpose, it may not be necessary for all vessels to be fitted with VMS units but that a representative subsample of different fleet sectors within each area could be fitted. This would be informed, in part, by the spatial logsheet data available in COMPASS, the fleet structure within the area, and local fisher's knowledge. However, it would not be appropriate to install VMS units on a subsample of the fleet in order to provide information on aspects such as potential overlaps in fishing areas (e.g. to aid in gear conflicts or spatial planning), the potential impacts on natural heritage interests (e.g. priority marine features or sensitive habitats), or for compliance reasons. Under these scenarios, it would be imperative that the majority, but in most cases all, the fleet are fitted with VMS devices. Spatial data at this level of detail may also be required to underpin assessments of sustainability, for example under accreditation schemes such as that provided by the Marine Stewardship Council.

There is also a commitment within the Inshore Fisheries Strategy for RIFGs to be able to provide fisheries advice to Marine Planning Partnerships. The Planning Partnerships may require fishing information for a range of different purposes and these may necessitate varying spatial scales and resolutions of data. For example, an evaluation of areas important to fishing within a marine plan can be presented with a fairly low level of resolution, however, the provision of spatial fishing data for licencing or development may necessitate much more comprehensive coverage, along with more considerable investment in data collection, processing and reporting. The potential level of engagement, and associated costs of providing fisheries data within marine planning processes should not be underestimated. Guidance on the utilisation and integration of fisheries data within the marine planning process, and the spatial scales which may be required, is set out in the following report and guidance documents (Batts, *et al.*, 2017b, a; Shelmerdine, *et al.*, 2017).

An additional consideration is the requirement for, and cost of, quality control of the spatial information. In the absence of additional equipment to monitor gear activity (for example RIFD tags on the winches of scallop dredgers), vessels with VMS units fitted are deemed to be fishing based on their speed profiles. Although the resultant spatial fishing footprint can be considered to be relatively accurate, errors will remain. These errors are mostly due to vessels slowing down when, entering harbour, sorting their catch/gear, within high tide areas, or rounding headlands. If the information is not quality controlled, this would lead to an overestimation of the spatial extent of the fishing activity. In some cases, this is easily resolved by removing perceived fishing data from within a set distance of harbours but this would have to be assessed on a harbour by harbour basis with the use of local knowledge as there are some harbours where fishing activity takes place within the approaches. Inshore fishers may also change their gear type to target other species. For example; scallop dredgers can also

fish for squid and demersal fish using demersal nets or hooks; and creel fishers may also jig for fish. Without an appropriate means of quality controlling the information, the inclusion of these other fishing activities would also overestimate the actual spatial fishing footprint.

5.3 Management requirements

As Bentley and Stokes (2009) articulate, trade-offs between the cost of collecting high quality and precision data and the management cost of such data collection are more straightforward to achieve if there are limited management choices. Where there are multiple, and perhaps conflicting management choices, it can be difficult for fishery managers to carry out such an evaluation and a formal mechanism may be required. In this respect simple, well-articulated, management aspirations may lead to more effective implementation of fisher led data collection programmes. If the aim of fisher led data collection is purely to enhance existing stock assessment programmes then a limited amount of data collection is required (see Section 3.2.2) and there would be limited costs associated with it. Should the data collection aspirations be to provide more detailed biological information with which to furnish locally specific data led reference points; a greater level of investment will need to be carried out and a judgement will need to be made on whether or not it is better to have a few vessels contributing a consistent time-series of data; or a greater number of vessels collecting time-limited data sets.

In taking forward decisions on the most appropriate resourcing to address any specific management measures, it is also important to consider possible additional costs which can include, but are not limited to:

- identifying and engaging participant vessels (which may require ongoing contact);
- fitting any electronic equipment to vessels (including costs of moving equipment between areas and vessels if data collection is time limited);
- training fishers to effectively use equipment and record data;
- processing analysing and reporting on the data (these costs can multiplied if the data are collected for more than one purpose e.g. marine spatial planning);
- maintenance of equipment;
- feedback and reporting to stakeholders.

As was demonstrated via the EFF project “Evidence gathering in support of sustainable Scottish inshore fisheries” (summarised in Section 4.1.1), effective stakeholder engagement is key to the successful outcome of fisher led data collection programmes and the value of this should not be underestimated when considering the costs associated with fisher led data collection programmes. It is suggested engagement and training should be continued periodically to reinforce best practice and to ensure that the data collected is viable and high quality.

5.4 Potential Sampling Design Methodology

Technical Appendix 5 outlines a method that can be used to leverage the statistical results presented here for improving sampling plans in the following situations:

- Port sampling
- Observers sampling at sea
- Sentinel vessels involved in new technology based -sampling programmes
- Sentinel vessels involved in self-sampling programmes

Technical Appendix 5 describes a sampling plan evaluation approach that is based on the port and trip sampling results produced here and makes some suggestions about how to extend this to cover observers, new technologies, and self-sampling programmes. In this evaluation system the results from Technical Appendix 1 are encapsulated in a spreadsheet which calculates the variance of the length proportions (sex disaggregated) for a given sample. This utility is called a Length Proportion Variance Calculator. The evaluation of the sampling plan involves considering logically feasible sampling plans, assessing their costs and benefits, and incrementally improving them in successive iterations.

6 DISCUSSION

Inshore (shellfish) fisheries in Scotland are generally considered to be relatively data poor. The aim of this project was to review current practice in shellfish data collection and stock assessment in order to provide objective information on optimisation using industry derived data. In this report we have outlined the current mechanisms for data collection and stock assessment; we have examined the data available to determine where additional sampling may be required and explored potential sources of bias in the assessment methods; a range of alternate sampling, stock assessment methodologies and management approaches have been considered, and some potential indicators discussed. The main findings of the study are that for some areas additional fisher led sampling would, when added to the current observer programme, add to the quality of data utilised in the stock assessment process. A potential method for designing data collection programmes, based on the analyses carried out in this report, has been suggested which includes methods for selecting sentinel vessels. We have also shown that, in the absence of reliable catch-per-unit-effort data, daily landings data can be used as a proxy for LPUE for Shetland. The reason for this is that in Shetland relatively small increases in the number of creels hauled per vessel occurred over time. The use of daily landings data as a proxy for LPUE in other assessment areas is justifiable if there is confidence that creels hauled per vessel has not increased to a degree that would invalidate this approach. This study was not able to comment on whether this condition is met.

The task of reviewing the current data available for assessment of Scottish shellfish stocks was considerable, and certain logistical difficulties were encountered. Accessing data was time consuming, and the initial tranche of data provided was not optimal for undertaking the necessary analyses to inform industry led sampling programmes (see Section 3 for data types). There were confidentiality issues around providing vessel ID information to the study, and there was thus no basis for carrying out vessel level analyses. This would have facilitated an investigation into the reasons for the frequently low sample sizes for crab and lobster samples (an issue with potentially important consequences for biological sampling). The inclusion of more detailed data with anonymised vessel ID information was deemed to be outside the time scope of this study by the time that the need for such detailed additional data was identified.

The majority of the data analysis has been carried out on crustacean length frequency data and Length Cohort Analysis (LCA) evaluation. This focus has come about for a number of reasons, but is primarily related to the greater potential for industry derived biological data for crab and lobster fisheries. The available data collection methodologies set out in Section 4 have not identified a definitive remote or fisher led sampling solution for *Pecten maximus* and although some potential solutions have been highlighted for crabs and lobsters, no system is currently in use. While video analyses have proven useful for other species of scallop, and Work Package 3 of the Scottish Inshore Fisheries Integrated Data System (SIFIDS) project is looking at novel methods for collecting additional scallop data for stock assessment there are no immediately applicable methods. It would be possible to use video techniques to provide size frequency data for scallops using a similar methodology as that proposed for the collection of crustacean data, however, this would not provide any age data on scallops. There is considerable variability in the growth rates of scallops (Chauvaud, et al., 2012) resulting mainly from variability in environmental parameters such as sediment type and current strength. Without some analytical method of incorporating these age related differences, fisher led data

collection for scallops may not yet be able to meaningfully add to stock assessment advice. This possibility of utilising an integrated stock assessment approach in this regard should be further explored.

Significant benefits for the introduction of fisher led data collection have been identified and these can be further taken forward at the local level, however this process needs to be driven by clear management aspirations. Critical questions which should be considered are:

- Should the focus of inshore data collection be to enhance the information gathered under the data collection framework, or should programmes be tailored to specific management units (and if so what should these units be)?
- What are the specific management questions which are to be addressed?
- Can the data be collected in such a way as to adequately contribute to different scales of management unit and differing purposes (e.g. RIFG fisheries management, MPP informing on location/impacts of development)?
- Is the purpose of additional data to enhance the existing stock assessment methods or should additional sampling be carried out for other purposes (e.g. data led indicators, alternative assessment techniques)? *This has the potential to greatly affect the volume of data which may need to be collected.*

6.1 Data Optimisation

6.1.1 *Length Frequency Data*

A quantitative study into the degree of precision of the length frequency data gathered in the biological sampling programme was carried out (see Technical Appendix 1). The approach taken was to restructure the biological dataset into a format in which there are different variable names for each length frequency, using the same 5 mm wide size classes that are used in the LCA analyses, but separate values for males and females (no gender distinction is made however for scallops). The sample counts in these length frequencies were converted to proportions, normalised separately for males and females. Thereafter, length class specific variance component analyses were carried out. The purpose of the variance component analysis is to obtain separate estimates of the contribution to the variance in the length proportions due to the following effects:

- 1) Month
- 2) Statistical Area
- 3) Assessment Area (note that the dataset that was analysed combined data from all assessment areas)
- 4) Gender (note that we treated gender as a separate “species” or “stock” consistent with the Length Cohort Analyses).
- 5) Year
- 6) Sample size per trip.

Factors one to five are provided relatively straightforwardly from the variance component analysis software. For factor six, trips were grouped into different “sample size” bins, making it possible to model of the relationship between the error variance and the sample size. These relationships and quantities made it possible to calculate the following outputs:

- 1) Mean Weighted Coefficient of Variance (MWCV) of the LCA range of length frequencies from the actual data, assuming stratified sampling, using month x statistical area as the strata.
- 2) MWCV of the LCA range of length frequencies from the actual data, assuming simple random sampling.
- 3) MWCV for a range of idealised situations, for different numbers of trips sampled, and different numbers of animals sampled per trip.

Two issues were contentious in these calculations: (a) the variability in sample size for points (1) and (2) compared to (3), and (b) how to address the component of variance due to month and statistical area. The details are fleshed out to some extent in the main text of this document. With regard to sample size, for crab and lobster, there are numerous trips where the sample size is very low. We conclude that if the expected design performance is to be achieved when following the advice either explicitly stated or evident in the various numerical results for idealised designs presented here, then it is imperative that the sample size be strictly controlled either by limiting sampling to vessels for which small sample sizes do not occur, or by oversampling in some manner. The issue is most serious for lobster where this advice should be heeded, but for crab this advice is also relevant. For scallops there seems to have been very good control over sample size over the last ten years.

With regard to the month (M) and statistical area (S) variance components, in principle a sampling design which is stratified by M and S eliminates much of the M and S variance, provided the design is implemented as such. This has not been the case, as often the number of trips that are sampled is low and hence the proportion of the M × S strata that have been sampled is quite low. The statistical implications of this have not been fully incorporated into all the results presented here. Since for crab the M and S variance component seems negligible, we carried out a brief investigation into what this might mean for idealised MWCVs for lobster and scallops. The effect was most striking for scallops, for which the M and S variance was larger relative to the error variances than for lobsters. For scallops (and lobsters) this did not change our assessment of whether a 30% target MWCV was being achieved by assessment area. Nevertheless, this topic deserves further investigation beyond this report. The main advice that comes out of this is that sampled trips should be spread as much as possible across different months and statistical areas but bearing in mind as well that sampling can only be done when and where fishing takes place.

The results from these statistical analyses provide information on assessment areas which are not being adequately sampled, and others for which there is too much sampling.

In addition to the length frequency data which could be collected to enhance the stock assessment programme, there may also be opportunities for fishers to collect additional data with which to calculate regionally appropriate biological input parameters for the assessment of crustacean stocks. This data collection would potentially involve additional research projects over and above routine sampling of the catch. Participation in mark recapture programmes for example could provide valuable information on growth rates and also valuable information on the structure of stocks, which is not currently considered within setting of assessment areas.

6.1.2 Spatial Data

The data which is currently collected at the national level under the Data Collection Framework, is not spatially reconciled with either the Regional Inshore Fisheries Groups or the Marine Planning Partnerships, both of which will be significant users of fisheries data in the future. It is commonly agreed that stock assessment methods should be linked to management aspirations and should optimise the use of available data (e.g. Punt, *et al.*, 2013) and therefore providing data at a suitable spatial scale is essential.

If fisheries managers are to consider the status of stocks at the national level, the reporting of fishing activity by ICES square would be a suitable spatial resolution, however, at the regional IFG level such a large reporting area would not be sufficient for most management decision making (Shelmerdine, *et al.*, 2017). Any management decisions required at a local level is likely to require more detailed information than is currently available through the FISH1 Form, paper EU logsheets, or the E-log.

For creel fisheries, spatial information on the setting of gear (including temporal aspects such as soak time) can be used to assess the potential impacts of gear saturation on the catch rate. This is not only useful in interpreting CPUE data, but can also be utilised in determining potential management measures such as gear limitation or spatial management of effort. A further benefit of spatial information would be in the evaluation of any management measures, for example the potential for displacement due to spatial closures, the impacts of/potential for gear conflict. With a sufficient level of data this evaluation process could be carried out prior to their introduction in order to optimise the approach with respect to the specific management aims.

Data on the footprint pf the scallop fishery, indicators of which could include the area of specific seabed types which was fished. There is a significant caveat in this approach in that it requires reliable information on seabed types, which is not always available from existing data sets and predictive habitat mapping (Shelmerdine and Shucksmith, 2015), and therefore the risks associated the quality of the underlying data used in this approach would need to be carefully considered. There may be opportunities for fishers to provide qualitative data about their knowledge of the seabed, to improve upon the available information. This is also an effective mechanism for engaging fishers in relation to potential management measures relating to the protection of vulnerable seabed habitats (Shelmerdine, *et al.*, 2014).

Fishers are known for their territoriality and in some cases, especially with creels and pots, gear are left in place either to ‘reserve’ that area for future fishing or remain in place due to a lack of suitable ground for the gear to be relocated. If VMS units were fitted to a subsample of the fleet, the resulting spatial information would not accurately represent the activity and extent of fishing within the area but rather would depict the spatial extent of the subsample only. The effects of this would be to underestimate potential impacts to priority marine features but, without knowing the full spatial extent of the fishery it would not be possible to utilise the information effectively in licencing and development applications, resolving gear conflicts, or monitoring fisher behaviour around closed areas, curfews, or sensitive habitats. Even a modelled or interpolated approach (i.e. where there is available information of vessel movements from a subsample of the fishing fleet but the spatial extend, or effort, does not completely cover the area so a model or interpolation is run to predict what the activity is within

these areas) would have significant drawbacks. This would especially be true if there was a requirement to assess the fishing impact or activity in relation to environmental conservation (e.g. priority marine features and sensitive habitats) or licencing and development applications. Such techniques would rely on the available data to be highly representative of the entire fishery which, as already highlighted for static gear fishers, is not realistic.

Mobile gear (scallop dredging) have additional considerations, relating to their spatial fishing practice, which may need to be taken into account. During a mapping exercise of scallop dredging around Shetland, all fishers were interviewed about their fishing practices and fishing areas (NAFC Marine Centre unpublished data). During this process it was evident that each fisher had their own technique for scallop dredging with some areas highlighted by many to be unsuitable for fishing, however one fisher independently noted these areas were good fishing grounds but in order for the fishing to be worthwhile, they had to alter their gear settings and their fishing practices. Although some of these alterations could be monitored for (for example, winch sensors to monitor warp length), others could not and are more a behavioural change by the fisher. Any proposed analysis would have to be aware of the potential impacts of fisher behaviour in interpreting spatial representations of activity and effort within the fishery.

6.1.3 Data quality, storage, and access

Access to data currently collected at the national level is time consuming and difficult due to resource limitations for data extraction and processing, and existing (and necessary) data protection mechanisms. The flow of data to be used in stock assessment and fisheries management is shown in Figure 2.4. The data are held in two centrally managed databases and access is via special requests. For both the FIN database and COMPASS the process of requesting data requires the signing of a data sharing agreement. Staffing levels and data sharing agreements for both fisheries and biological data can mean that data requests may not be facilitated quickly, data may only be released for a specific purpose, and it may not be possible to share the data at the level of detail required, or over required time series. For data that may identify individual fishers it may be necessary to get written permission from them prior to accessing the data, for a fleet the size of the Scottish inshore fleet this could be impractical even at the regional level.

Any sampling programme proposed for future data collection is likely to require a time series of historical data in order to carry out analysis/interpretation, to observe trends in fisheries, and to determine the impacts of any management measures. It is therefore important that any new data collection plan considers access to, and compatibility with, historical data as part of the process, particularly with regards to reporting. It is also important that any data collection programme considers the availability of, and access to, the data produced going forwards, to make sure that the consideration of best value can be adequately incorporated in to decision making. This will require careful consideration of consent and data ownership where stakeholders are providing data, and also of data entry, storage, processing and reporting. This is not only useful in routine stock assessment, but is also particularly important for management enquiries which are additional to routine monitoring and stock assessment. The automation of data submission utilising electronic methods has the potential to speed up data entry, and the potential to generate large volumes of data, however, assessing the quality of the data and evaluating any associated risks would be crucial to the data being useable.

Adequate data policies should be in place to ensure timely dissemination of data for scientific and management purposes, while ensuring confidentiality. This is essential for all fisheries related data sets and would be aided by ensuring data are kept up to date. It will also be important to identify and prioritise those data processes which will require a high level of time input to ensure that analysis and reporting is timely, and best value can be obtained from the full range of data which is available. Aspects such as understanding and assessing any risks related to the delivery of data outputs and analyses that are associated with both the time taken to input data and to peer review assessment methods and outputs are also important (Bentley, 2015).

To facilitate greater, and more timely, access to data it may be that fisher led data collection programmes make use of data storage and management systems which lie outside the current data storage and management system. That is not to say that the outputs of fisher led sampling could not be utilised to supplement the existing stock assessment programme, but rather that there would be inherent benefits in the data being more readily available for other uses. For example the production of data led indicators and reference points can be very useful in management, and the more recently the data was collected the greater its relevance to any management decisions being made. In examining this possibility it is also important to consider data management and analysis. The Shetland Shellfish Management Organisation commissioned a bespoke fisheries management database (Shetland DDM OLSPS) which can store both fishery and biological data and can present data within a map based interface. The data in the system is available as soon as it has been entered and quality checked, and therefore provides “real time” information to aid in management decision making, as opposed to stock assessment reports and analyses which may rely on extraction and external processing of data prior to the presentation of results. This approach may not be economically justifiable for all areas, and the accessibility software and its licencing may need to be considered; however, the development of data management systems which can provide rapid feedback on up-to-date data are an important consideration when designing new data collection programmes.

If data collection programmes are designed within specific management units (e.g. RIFG's) there will need to be consideration of data sharing. For example where vessels may be fishing in one area but landing their catch in another, or where fishing activities straddle the boundary between different management units. It may be that RIFGs can take a more prominent role in managing data collection and can provide a more regional approach to permissions. For example it may be possible for a general data sharing agreement to be undertaken between fishers and the RIFG whereby sensitive data can be stored and utilised at the local level but would not be made available more widely without specific permissions being in place. Conversely it may be possible for RIFGs to obtain a greater level of access to national databases such as COMPASS, under clearly defined conditions to speed up the process of accessing fishery data, and to reduce the burden of data requests at the national level.

6.2 Stock Assessments

A review of the stock assessment methods used for lobster, crab and scallop stock was carried out. Assessments for lobster and crab use Length Cohort Analyses (LCA), which is based solely on length frequency and catch data, and makes the strong assumption that the stock is being fished under equilibrium conditions. F_{MAX} , based on yield-per-recruit analyses is the

target reference point for fishing mortality for these stocks (although reference points have not been explicitly set for management purposes). Since the limitations of stock assessments based on catch-at-length data only are widely reported in the literature, and since the available stock assessment reports do not report a CV for the LCA based fishing mortality estimate, a numerical study was carried out to try to quantify the bias and precision of LCA based estimates of fishing mortality. Two separate studies were carried out, one into bias, and another into precision. These are reported as Technical Appendix 2 and Technical Appendix 3 of this report. The bias study indicated that, were the LCA to use assumptions about natural mortality and growth rate which are different to those pertaining to the underlying stock, then there would be bias in the fishing mortality estimates. This bias may however be mitigated by the yield-per-recruit analyses which are used to establish a value for F_{MAX} , since both F_{MAX} so determined and the fishing mortality estimates are likely to be biased in the same direction. The investigation into bias concluded that the most serious potential cause of bias for LCA is the failure of the equilibrium assumption, something that was perhaps self-evident at the outset.

The investigation into the precision of LCA estimates had a two-pronged aim. The first was to define and establish the usefulness of a collective measure of the imprecision of the length frequency data, a quantity referred to here as the Mean Weighted Coefficient of Variation (MWCV) which has been used in other similar studies. The second was to establish a link between MWCV and the imprecision in fishing mortality estimates derived from LCA. This work and the results are presented in Technical Appendix 3. The simulations involved the extensive generation of artificial data with multinomial distribution properties. The results suggest that the LCA estimates of imprecision are fairly robust to MWCV values that would be considered large from a sampling point of view. The reason for this robustness is thought to be that LCA uses a three-year averaged length frequency distribution, and the back-calculation procedure in LCA, much like VPA, attenuates the scale of error in fishing mortality estimates as the calculations progress further to small length classes. This study (see Technical Appendix 2) indicates that an MWCV of somewhere in the range 20% to 30% will guarantee a CV on F estimates from the LCA method of less than 20%. From this perspective, and a the notion that the sampling CV, i.e. the MWCV, should not be larger than 20% to 30%, suggests that the design criterion for sampling for length frequencies should be to achieve an MWCV of less than between 20% and 30%.

As mentioned, LCA (Length Cohort Analysis) is based on catch-at-length data and makes the strong assumption that the resource is being fished under equilibrium conditions. In general if there are any changes in CPUE, catch or effort, then the equilibrium assumptions is not valid. The two most important data sets required to calculate CPUE are the trip catch (either daily or weekly) and the corresponding number of creels hauled (i.e. the effort). Also of importance is associated information on vessel ID, soak time, and fishing location. With the exception of Shetland (where LPUE data are available), the existing data that has been captured for Scottish inshore fisheries for lobster and crab does not currently provide a complete and adequate record of creel hauls to make it possible to calculate CPUE. This is not to imply that in the future the use of a small subset of representative vessels cannot provide an index of CPUE. However, as this is not available in the historic data sets it will take some time to build up this index from data gathered via the FISH1 form (Figure 2.1). The issue then is what might be possible in the interim period. This topic is developed further here.

It is important to recognise that within the current system, data submitted on logsheets will provide information on landings per unit effort (LPUE) only, as they do not record the discard component of the catch. Should management requirements necessitate the use of a catch per unit effort (CPUE) data set, then additional data collection would be required and this could be carried out by a representative subset of fishers.

An alternative to CPUE (or LPUE) that is used in certain crustacean fisheries (for example the South African West Coast rock lobster fishery, for the dinghy fleet) is to use the daily catch per se as a measure of catch rate, CPUE. Comparative analyses were carried out for LPUE and daily landings for Shetland in order to test the assumption that daily landings can be a useful proxy or alternative to LPUE. The GLM analyses in Technical Appendix 4 showed very high correlations between LPUE and daily landings, suggesting that daily landings is a potential useful indicator of sustainability in other assessment areas for inshore Scottish fishery. Landings and LPUE trends are however likely to diverge under conditions where there are systematic increases in the number of creels hauled per vessel per day over time. The possibility that this has happened for Shetland was explored by means of GLM analyses of effort level (see Technical Appendix 4). The conclusion is that there have been very small increases in creels hauled of less than 1% per annum. The conclusion is thus that daily landings could serve as an index of LPUE, for Shetland specifically. It is not clear if this lack of trend in the number of creels pulled per day per vessel is representative of the trends in creels hauled per vessel in other RIFG areas, so the issue remains somewhat unresolved. Local fisher's knowledge could potentially be utilised to determine if this approach would be appropriate for other areas. As mentioned above, this suggestion should not exclude or be taken to imply that other options do not exist, for example to make use of CPUE data from a limited number of vessels who report effort data as well as catch information. The understanding of this project is however that such information is not available elsewhere at the present time, other than in Shetland.

Given current data availability there are limited options for alternative assessment approaches for crab and lobster stocks, namely LCA and daily catches. Both of these would be limited in their ability to provide stock assessment quantities of value for management when there are systematic increases or decreases in effort, and certainly the use of daily catches or daily landings needs to take account of discards to the extent possible. The issue of catches or landings as the basis for CPUE depends however on what the reason for the discard is/was, and the survival rate of discarded animals. These factors can be defined in the stock assessment analysis, e.g. landings are specific to animals above the minimum size.

Some possible alternative stock assessment methods are suggested here for application to crab and lobster stocks, namely the use of length based dynamic methods in which the growth process is explicitly modelled (see Punt, *et al.*, 2013). These methods should only be actually used in management decision making if they incorporate and analyse indices of abundance such as daily catch or CPUE or a survey abundance index. If this is a vision for the future then incorporating such methods into the management suite for crab and lobster would be recommended. In initial work, in the absence of, say, CPUE or survey abundance, their management usefulness may be very limited. They would nevertheless at an early stage serve a valuable purpose by highlighting (a) important biological information that may be lacking, (b) the nature and extent of assumptions implicit in the present management system. In addition, since these methods are highly scalable with respect to the nature of data that can

be included in the analyses, they will be able to grow and evolve over time to accommodate additional data types as these become available.

The assessment method used for scallops is a state-space model known as TSA. We understand that this method is relatively flexible with regard to the data types that can be incorporated, and also that the method uses catch-at-age data, as well as information on the relative abundance (at age). These two kinds of data are the most highly rated data types in stock assessments and so it is felt that the approach is sound and adequate for management purposes. It rates above the approach taken in the north east USA where a size-based method (CASA) is used in the stock assessments. The only disadvantage with TSA compared to the other general integrated stock assessment approaches (IA) used elsewhere is that the methodology and the software is less accessible than IA. The usual platform for IA is ADMB or TMB, both freely available online. In addition, there are a number of completely free stock assessment templates designed to work with AD Model Builder (ADMB), e.g. Stock Synthesis. TSA as we understand it requires the use of a proprietary software platform, Numerical Algorithms Group (NAG) (H. Dobby pers. comm.). The result is that the skills for application of TSA are less wide-spread, and this may become a limiting factor in certain circumstances. For this reason, we do recommend the additional use of IA methods, and in any case it would be very useful to compare the results obtained using IA with those from TSA.

6.3 Indicators

Industry led sampling programmes have the potential to provide significant contributions to an indicator approach. This is particularly the case in empirical indicators which can be derived from a variety of fishery and biological data sets. For example there would be benefits to the assessment and management of both crustacean and scallop fisheries in the provision of an estimate of the proportion of the catch which is undersized, which is not recorded via observer sampling on shore. Data led indicators can be utilised in fisheries management in a timely and transparent manner. However, the lack of a biological basis for reference points can cause problems for managing stocks to MSY.

Crab and lobster fisheries in Scotland are considered to be data poor and rely predominantly on fisheries dependent data and Miethe, *et al.* (2016) indicate that the development of indicators for these stocks would be beneficial. They recommend that length based indicators would be the most appropriate for crustacean fisheries, although the authors point out that interpretation of the data (for which no survey data are available) should be carried out with caution as it would be collected in a non-standardised way, although the collection of standardised data could and should be built into any future industry derived sampling programme, whether it be across all participating vessels or a subset of 'sentinel vessels' within a reference fleet. Other biological data such as moult stage, reproductive status and sex ratio data could also be collected alongside length data and can be readily utilised as stock indicators in fisheries management.

Scottish scallop stocks can be considered data rich due to the presence of both fisheries dependent and fisheries independent data (Miethe, *et al.*, 2016), however, it is acknowledged that assessments cannot be carried out for all areas. Here the authors suggest that the output of survey data could be utilised to provide indicators of abundance and recruitment at a finer spatial scale. The use of industry gathered data for scallops would not necessarily be able to

provide age data for assessment, but would have the potential for remotely gathered size frequency data and could provide additional abundance data and information on recruitment to the fishery. It is likely that spatial indicators could provide useful for the management of the scallop fishery, particularly in relation to the footprint of the fishery. This type of data can be utilised in the identification of discrete fishing grounds, which can provide spatial context for both landings and effort data, but also be used to contribute to survey design. Spatial indicators for scallop fishing can also be utilised in the context of marine environmental protection as set out in the inshore fisheries. It is important to recognise that industry derived data is representative of the fishery, but that this may not represent the full extent of the stock.

6.4 Management

While it is important to investigate the value of a sampling programme with regards to the quality of the data collected, it is also important to determine the benefit in terms of achieving management aims (Bentley and Stokes, 2009). It is often difficult to fully evaluate the costs versus the benefits of moving fisheries from a data poor situation to one which provides sufficient data for effective management. As Scottish Inshore Fisheries Management moves from a nationally controlled licencing programme to a more regional approach, the need for clear links between management objectives and the outputs of any industry derived data collection programmes will be important in achieving aims.

Mackinson, *et al.* (2017) reinforce the assertion that the design of data collection programmes should meet the needs of the system for which the data are required. If the information is to provide sufficient evidence to support fisheries management and stock assessment, then it will have to be collected under the required protocols to fit the data collection framework. If the data are required to provide information in support of sustainability and environmental credentials, then accurate catch and fishing activity data will be required.

In order to assess the success of data collection programmes effective monitoring and feedback mechanisms within the fisheries management process are necessary. The value of data collection programmes can be significantly reduced if there are not mechanisms in place within the management framework to implement recommended management changes, monitor their effects, and carry out modifications if required. This process should be a continuous feedback loop.

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Stock Assessments: crab and lobster

- 1) The most serious source of bias in the Length Cohort Analysis (LCA) methodology is the potential failure of the equilibrium assumption upon which these calculations are predicated.
- 2) For lobster and crab stocks, until such time that adequate data on creel effort is available, suitably GLMM standardised daily catch should be used as a proxy for CPUE for crab. Creel effort data will become available through COMPASS or could be derived from a subset of reliable vessels for the purpose of the estimation of CPUE.
- 3) Stock assessment methods such as Replacement Yield (RY), surplus production modelling and integrated size based assessment models which can make use of these CPUE proxy data should be trialled, initially complementary to the prevailing LCA methodology. These methods should, in the first instance, be used to test the equilibrium assumption of the LCA methods. Should these methods indicate that the resource is clearly not being fished at equilibrium, then further reliance should be placed on the results of these alternative approaches, moving away from the LCA approach.
- 4) For lobster and crab stocks, the performance of the relevant stocks in relation to target reference points that are compatible with the stock assessment methods proposed immediately above should be developed.

7.2 Stock Assessments: scallops

- 1) For scallops integrated stock assessment analyses should be run in parallel with the TSA assessments.

7.3 Biological sampling: general

- 1) The Mean Weight Coefficient of Variation (MWCV) is an adequate measure for quantifying sampling errors in length frequency estimates.
- 2) A target MWCV for the annual length frequency samples should be set at between 20% and 30%, for crabs, lobster and scallops, by assessment area and stock. This applies separately for males and females in the case of crab and lobster stocks.
- 3) The number of trips to be sampled and the number of samples per trip in order to achieve the target MWCV of between 20% and 30% are indicated in the results produced in this document, see Table 10.20 (Lobster), Table 10.21 (Crabs), and Table 10.22 (Scallops). Use of these quantitative recommendations should bear in mind that the recommended sample sizes per trip that are presented here do not assume that the sample sizes are averages, but rather that they are exact. Given the results in Table 10.23 (Lobster), Table 10.24 (crab) and Table 10.25 (scallops) which shows that the variation in sample size per trip increases the MWCV, the sample size should be controlled to be no less than the value shown in Table 10.20 to Table 10.22. This may only be possible by either (a) oversampling, or (b) sampling vessels that achieve a large enough catch to provide the required sample size. There is a potential trade off here between the introduction of potential bias in sampling by only collecting data from larger vessels, and in limiting the quality of the data by sampling a range of vessels including those with smaller catches in order to reduce that potential bias. The cost implications of each approach, depending

on the system to be used, would need to be considered and would be an appropriate area for consideration in any follow on work.

- 4) In general, sampling of trips should try to ensure as much coverage across months and statistical areas as possible.
- 5) It would be recommended to sample a range of vessels and it is more important that an appropriate vessel selection procedure be implemented, rather than simply increasing the number of vessels.

7.4 Biological sampling: lobster

- 1) For lobster, Clyde and North Coast are not meeting the 30% MWCV threshold because only one trip was sampled there in 2016.
- 2) For lobster, in order to meet the 30% threshold at Clyde, for the same number of individuals sampled (10 for females and 16 for males), the number of trips needs to be increased from one to between five and 10 trips per year.
- 3) For lobster, in order to meet the 30% threshold at North Coast, for the same number of individuals sampled (34 for females and 14 for males), the number of trips needs to be increased from one to between three and ten trips per year.
- 4) For lobster, it is not feasible to reach the 30% MWCV threshold at either Clyde or North Coast by increasing the sample size per trip, although this is possible if three trips are sampled and the sample size per trip per sex is increased to at least 30 each.
- 5) For lobster, sampling can be reduced moderately at South Minch and substantially at Orkney and an attempt should be made to transfer these extra sampling resources to Clyde and North Coast.

7.5 Biological sampling: crab

- 1) For crab, a 30% MWCV threshold is not being achieved at the Clyde, South Minch, and Ullapool.
- 2) In order to meet the 30% threshold at Clyde, about five trips need to be sampled for crab, and no trip should sample less than about 40 crabs per sex (within the LCA size range).
- 3) For crab, in order to meet the 30% threshold at South Minch, for the same number of individuals sampled (30.5 for females and 39 for males), the number of trips needs to be increased slightly (the design results suggest that to be safe six trips should be increased to nine trips).
- 4) For crab, at Ullapool the number of trips should be increased from three to about five trips. The sample size per sex and trip should not be less than 76.
- 5) For crab, excessive sampling is taking place at the following locations: East Coast, Hebrides, North Coast, and Orkney and a reduction in the sampling at these locations (especially the number of trips sampled) should be used to increase the amount of sampling at Clyde, South Minch, and Ullapool.

7.6 Biological sampling: scallops

- 1) For scallops, without taking consideration of adjustments for month and statistical area components of variance, the 30% MWCV threshold is not being achieved at Clyde and Orkney (for 2016).
- 2) Achievement of an MWCV of 30% cannot be achieved by increasing the sample size of scallops per trip above the amounts achieved in 2016, and should instead be achieved by increasing the number of trips sampled at Clyde from three, to between five and ten. The same applies for Orkney.
- 3) In the case of scallops, the additional variance due to month and statistical area must be accounted for in order to determine sample sizes per trip and the number of trips that should be sampled.

7.7 Optimisation Recommendations

Given the above recommendations based on the current data, the following issues, which are interlinked, need to be fully and clearly specified in any industry led data collection plan in order that each can take the appropriate direction from the other:

- Determination of the nature and quality of data that needs to be collected from the fishery and the resource – this will relate specifically to the management aims.
- The stock assessment approaches that are used, their data requirements, and which of their outputs are to be used in management.
- The management approach that is used, and probably the fishing rights access regime in place, quantified target and limit reference points if relevant to the management approach.
- The translation of the management approach into a specific and enforceable fisheries control mechanism.

A recommendation of this report is that Marine Scotland work closely with RIFGs to determine priorities at the regional level which can then be used to devise regionally appropriate sampling protocols which can provide data that is suitable both for the stock assessment programme and also to address management aims.

Clear strategic direction with regards to the overarching requirements for data should be provided in order that any investment in fisher led data collection programmes can be implemented in the most cost effective manner. This strategic direction should indicate objectives for fisheries management, ecosystem objectives and marine planning interactions.

The purpose of any industry led data collection should be effectively communicated to all potential participants at the start of any project and the data ownership and management protocols identified and agreed.

The processes for storing, managing, analysing and reporting on data should permit information to be used in the most effective manner possible, and to maximise outputs. It is likely that additional mechanisms to those currently used for the national data collection programme will be required, and data compatibility between systems should be considered early in the sampling design process. Data ownership and consents for use should also be considered.

The implementation of any new system for data collection should be regularly evaluated to determine its performance against fishery management objectives and should be open to peer review. Where possible this should include simulation modelling for different management scenarios (where appropriate and cost effective this should be done at the RIFG level).

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TECHNICAL APPENDICES

10 TECHNICAL APPENDIX 1

10.1 Overview of methods

This appendix describes the methodology that was used to calculate the precision of length composition estimates provided by the biological sampling programme. Because the results that were obtained indicate poor precision in a number of cases, the methods, which are described algebraically and notationally further on in this appendix, are first summarised in an intuitive verbal fashion, highlighting assumptions and methods that may cause the methods to produce biased or incorrect results.

Although variances can be calculated from within sample methods as is typical for random stratified sampling schemes, the aim here was to provide some insight into the different components of variance in order to perhaps eliminate certain sources of variance and to inform recommendations about alternative sampling designs. Thus we followed an approach which brought with it considerable complexity, but which made it possible to attach a variance estimate to the proportion estimates for each length class of a single trip. A description of the uncertainty of the multidimensional “length frequency” is not well settled in the literature, hence the need for some novelty regarding methodology. Here we have proposed the use of a collective quantity, Mean Weighted Coefficient of Variation (MWCV), to describe the precision of the length frequency estimates by a single number. For a normalised length frequency, i.e. where the proportions of the length frequencies sum up to 1, the MWCV is the sum of the proportion p for each length class, multiplied by its CV, summed up over all length classes. It is a convenient single quantity for referring to the uncertainty in length frequency distributions (see also Bergh, *et al.* (2009)). Technical Appendix 4 reports the results of a simulation study to establish a link between the MWCV and the CV of fishing mortality estimates obtained using LCA. The initial objective has been to describe the MWCV associated with the existing sampling data, and then to go on to describe how the MWCV varies across a range of alternative sampling approaches. The methods to calculate the MWCV for the existing sampling schemas have involved the following steps:

- Definition of a “sample” as being derived from a single trip.
- Restructuring the data so that the proportion of individuals for each trip within the same set of length classes that are used in the LCAs are available in an analysis ready format.
- Treatment of the variance components of each length class as unique.
- Use of the R algorithm GLMER (Generalized Linear Mixed-Effects Models), which runs Generalized Linear Mixed-Effects Models (GLMMs) to estimate the variance components for statistical area, month, season, year, gender and assessment area, by treating these variables as random effects. This model used a binomial distribution with a logit link function. We were unable to successfully run Minimum Norm Quadratic Unbiased Estimation (MINQUE) on these data in the “proportion” domain, hence the use of GLMER.
- Binning the variance component analysis by different sample size bins, in order to develop relationships between error variance and sample size per trip sampled. These are unique relationships for each length class in the LCA analyses. Five bins were used and this was considered adequate to estimate the variance components as well as track their dependence on sample size.
- Fitting smoothing models to the relationships between sample size and error variance in the logit domain – “Logit domain error variance models”. These models were checked to ensure that interpolation and/or extrapolation did not give rise to “out of

“control” values when used for sample sizes different to those involved in the fitting process. In addition, the sample size was capped to be no larger than the mean for the largest sample size bin to further prevent “out of control” extrapolated error variances – this is reasonable since most relationships tend to show asymptotic behaviour for the error variance at large sample size, implying residual trip to trip variance that cannot be eliminated by increasing sample size any further. We also checked that at a sample size of 1 the value was not any larger than would be implied by extrapolating from the smallest sample size bin down to a sample size of 1 using the multinomial distribution assumption, i.e. variance proportional to the inverse of sample size.

- Returning to the original “restructured datasets” in order to enrich them with estimates of the error variance associated with each length class in each trip. This involves using the “Logit domain error variance models” to calculate the “p” domain error variances. A special user defined function (UDF) was developed in Excel to translate the “logit” domain error variance to “p” domain error variances – the UDF makes provision for a bias correction factor as described in more detail later on in this appendix”. At this point an implicit assumption is highlighted, that the error variance in the “logit” domain is independent of the “p” domain sample proportion for a particular sampled trip. Note that nevertheless the UDF results in different error variance in the “p” domain for different values of p, even given the same “logit” domain error variances.
- For the final MWCV, different calculation methods can be followed. We were able to merge the landings data and the biological data at the level of month and statistical area and could therefore implement a post stratification schema which treats unique combinations of month and statistical area as the strata, for which catch weights are available from the merge to the landings data. At the month/statistical area level of resolution, the vast majority of strata are not sampled for most assessment areas. The variance of the mean proportion for each stratum (and length class) is the sum of the variances for each sample divided by the square of the number of trips sampled per stratum. The variance of the stratified mean is the sum-product of these stratum variances by the square of the normalised catch stratum weights. Given that many month x statistical area strata in which catches took place were also not sampled, the catch weights are renormalised such that they sum to one across all strata which were sampled, before completing the MWCV calculations.
- The CV for a particular length class is the square root of the variance obtained at the end of the last step, divided by the stratified mean proportion (details not given since this mirrors the variance calculations). However, because the MWCV is the sum-product of these CVs and the stratified mean proportions, the MWCV is given alternatively as simply the sum across all length bins of the square root of the stratified variance. We assumed that when the mean proportion for a length bin falls below 1% then the variance components are unreliable and in any case these would contribute very little to the MWCV. Thus the summation for MWCV was only run up to the length class before the mean proportion falls below 1%.

A number of variant calculations were carried out and the rationale is presented here:

- 1) Excluding month, statistical area and season from the variance component analyses (VCA). Although in principle stratification by month and statistical area eliminates/reduces the variance due to these factors, this does not hold when there is incomplete sampling of all strata in which fishing occurred. The full implications of this have not been calculated here, and therefore we calculate MWCVs both ways, either

with or without month/statistical area/season included in the GLMER model used for the VCAs.

- 2) Weighted and unweighted GLMER analyses. GLMER can be set up to take as a target variable the proportion (unweighted), or alternatively the number of samples and the number falling within the length class of relevance (weighted). The latter would clearly ascribe more importance to larger sample sizes in the estimation of the variance components. Results for both methods are compared.
- 3) Simple random sampling. We found little difference between the stratified MWCVs and those based on the assumption of simple random sampling (i.e. a single stratum). In some cases we report simple random sampling results.
- 4) Double the number of trips, and Double the sample size: MWCV calculations are produced where either the number of trips, or the number of samples, is double the number given in the raw data, as a first step to see whether it is possible to circumvent the need for sampling more trips by increasing the sample size per trip which is assumed to be a cheaper option.

A note about covariances: Covariances have not been explicitly addressed in the calculation schema described above. However, the simulations presented in Technical Appendix 3 generate samples drawn from a multinomial distribution, and so the appraisal of the MWCV required to achieve estimates of fishing mortality of adequate precision as presented in Technical Appendix 3 has underlying multinomial covariance between realizations of sample proportions in different length classes. The MWCV calculations produced here are intended partly for comparison to the results in Technical Appendix 3, to determine whether the MWCV precision calculated here provides for adequate fishing mortality estimation precision from the LCAs. Implicit in this comparison is that the covariance structure of the biological samples is equivalent to multinomial covariance of proportion estimates between length class, at a sample size commensurate with the MWCVs and mean proportions reported here. In short the claim being made is that covariance has been “implicitly” addressed.

10.2 Detailed methodological description. Variance component analysis of length composition data, estimation of overall MWCV for annual length composition data, MWCV for alternative sampling designs.

The purpose of the following is to describe the methods in some more detail according to the following sections:

- 1) **Variance components analysis:** To estimate the variance components of the length composition data for the size range relevant to the LCA analyses, and with respect to variables that exist in the sampling data and are relevant to possible alternative sampling designs.
- 2) **Variance of existing sampling programme:** To estimate the total variance in the length composition data, as quantified by the value of MWCV, and to comment on whether this value provides sufficiently small CVs to obtain fishing mortality from LCA that have an acceptable degree of uncertainty.
- 3) **Variance of alternative sampling designs:** To develop a methodology to explore alternative sample designs for the length composition data, to report on a number of these alternatives, and to provide guidance for improving the sample designs.

10.2.1 Methods - Variance component analyses

For lobster and crab stocks, the catch-at-length information used for the LCA analysis are derived from annual biological samples. These biological samples were supplied to OLSPS Marine as raw sampling data by Marine Science Scotland. The data covers the period 2006 to 2016. The following variables appear in the sampling data, or could be derived from other variables available in the sampling data:

- 1) Management area (A)
- 2) Statistical area (SA)
- 3) Month (M)
- 4) Season (S)
- 5) Gender (G)
- 6) Year (Y)
- 7) Trip ID – a unique identifier for a trip.

The data were restructured so that each case (i.e. record or row) in the data represents a unique combination of trip ID and Gender, and columns were added reflecting the proportion of animals measured and found to lie within each of the length classes between L_{\min} and L_{\max} . All animals smaller than the lower length class L_{\min} were excluded from the analysis described here since these are not relevant to the LCA analysis investigated in Technical Appendix 2 and Technical Appendix 3 of this document. A variable N was created which is the total number of animals measured as falling between L_{\min} and L_{\max} , for each case.

Different algorithms were considered for carrying out the variance components analysis for the proportions for each length class. The relevant variance components are those associated with points 1 to 6 listed above, i.e. they are designated here as σ_A^2 , σ_{SA}^2 , σ_M^2 , σ_S^2 , σ_G^2 and σ_Y^2 .

The application of MINQUE for the variance component analysis was unsuccessful. The R-routine GLEMR was run successfully. In this analysis the variance components due to each of σ_A^2 , σ_{SA}^2 , σ_M^2 , σ_S^2 , σ_G^2 and σ_Y^2 can be obtained from GLMER by specifying these components to be random effects – the variance component is then the variance associated with the random effect. The algorithm was run using a binomial distribution and a logit link function. The variances for each of the random effects are given by GLMER for the logit transformed proportions. GLMER does not report the error variance in either the logit transformed or untransformed space, but we calculated this variance as the variance of the difference between fitted and observed proportions, both in the “p” domain, or in the “logit” domain.

Some initial estimates of variance components are presented in Table 10.1 for lobster, but excluding the Shetland management area (because the values of L_{\min} and L_{\max} for Shetland are different to those of the other assessment areas which share common values of L_{\min} and L_{\max}).

Results in Table 10.1 suggest that the error variance dominates, and this raises the question as to what drives the error variance. The dominance of the error variance could be due to one or both of the following;

- a) Trips differ inherently and substantially with respect to length composition even if they are in the same area, month, year etc, or
- b) There is insufficient sample size per trip, and this is the main cause of the relatively large error variance.

If (a) is true then increasing the sample size per trip will not be able to reduce the error variance. The only option would be to increase the number of trips that are sampled. This is an expensive option.

If (b) is true, then increasing the sample size per trip will reduce the error variance. This is a less expensive option.

The difference between (a) and (b) is central to this study since it has a bearing on the utility of various schemes that are being proposed to increase the efficiency of sampling effort per trip. (b) would support the further development of and eventual introduction of these innovations, whereas (a) would favour sampling more trips not necessarily focussing solely on increasing the sample size per trip.

Some preliminary investigation into the size of the contribution of the error variance was carried out. Two separate runs with GLMER were carried out:

- 1) One run was for a trip level sample size $N \leq 25$, which has a mean sample size of seven,
- 2) The other was for a trip level sample size $N > 25$, which had a mean sample size of 54.

The results of these runs are summarised in Table 10.1.

These results show that the error variance is six times smaller for $N > 25$ (N mean = 54.42) compared to $N \leq 25$ (N mean = 7.69). This shows that the sample size per trip is critical to the quality of the length comp data, across a range of sample sizes between 0 and 100, which is perhaps an obvious result. For $N_mean = 54.42$ there is nevertheless still some error variance (0.535) which we may wish to ascribe to trip to trip variance distinct from trip level sampling processes and sample sizes.

By viewing results over all length classes and for different values of N_Mean , the intercept and the untransformed mean proportion, it is hoped that it may be possible to develop a parsimonious view of the variance components, perhaps incorporating the following two features:

- Error variance in logit space depends only on N_Mean .
- All variance components other than the error variance are constants in “logit space”.

In such a situation a fairly straightforward simulation schema can be developed to calculate the variance (MWCV) of the existing sampling programme, and the variance (MWCV) of alternative sampling programmes.

To assess questions about the level of complexity that is required to adequately describe the relevant statistical processes, a more comprehensive analysis of the variance components across all length classes was carried out. The results are summarised in Table 10.2 for the situation where three sample size bins were used. Amongst a number of features, the results indicate that for larger length classes, the results are unreliable since the amount of available data becomes too small – in particular because of the high proportion of records which have a zero proportion. In order to more clearly discern whether the error variance is tending to zero at large N_mean values, or whether there is a finite residual value, the number of bins of N_mean was increased yet further. These results are shown in Table 10.2 (three sample size bins only) and Table 10.3 (five sample size bins).

10.2.2 Methods - Variance and MWCV of the existing sampling programme

In order to estimate the sampling variance inherent in the existing catch sampling scheme, it was assumed that the annual catch length composition estimates are post-stratified means. For these analyses, stock and gender specific analysis were carried out, and it has been assumed that the relevant strata are month x statistical area combinations. For the stratified mean the following calculation procedure is followed:

- 1) The mean length composition is calculated for each stratum, $\bar{p}_s = \frac{\sum p_{s,i}}{N_s}$.
- 2) Let the stratum weights be w_s . The stratified mean length composition \bar{p} is calculated as the weighted sum of the stratum means, i.e. $\bar{p} = \sum_{s \in (1, K)} w_s \bar{p}_s$, where the weights are pre-normalised so that they sum up to 1, $\sum_{s \in (1, K)} w_s = 1$. The weights are the proportion of catch per stratum in each year for which biological sampling data are available, i.e. 2006 to 2016.

The calculation of the variance of the stratified mean uses the following calculation steps:

- 1) Let $p_{i,s}$ be the i-th observed proportion for stratum s, for an unspecified length class and year. There is a total of K strata, and s is the stratum index, $s \in (1, K)$. There are N_s records in stratum s, and i is the within stratum index, $i \in (1, N_s)$. The sampling variance of $p_{i,s}$ is calculated using quantities derived from the results of the variance components analysis (VCA), as follows:
 - a) In logit transformed space (denoted by the subscript z) the variance due to month, $\sigma_{i,m,s,z}^2$, is as given from the VCA, and this value is specific to a length class, except for larger length classes for which VCA was considered to be unreliable. **This variance need not be considered for a stratified sampling design, but would be relevant to a simple random sampling design.**
 - b) In logit transformed space the variance due to statistical area, $\sigma_{i,a,s,z}^2$, is as given from the VCA, except for larger length classes for which VCA was considered to be unreliable. **This variance need not be considered for a stratified sampling design, but would be relevant to a simple random sampling design.**
 - c) In logit transformed space the error variance, $\sigma_{i,error,s,z}^2$, is as given by the VCA, where a formulaic adjustment is used to calculate the error variance for a specific sample size (i.e. number of animals sampled) for record i in stratum s. The development of this formula involved fitting the error variances in the tables Table 10.5 to Table 10.12 as a function of the sample size for each of the five bins of sample size. The resulting non-linear regression equation is a “smoother” which makes it possible to calculate the error variance for sample sizes values other than those shown in the variance component tables. A different set of parameters of this smoother was obtained for each length class. For lobster the equation that was used was $\ln(\sigma_{error}^2) = (A * \text{EXP}(B * N) + C + D * N * N)$, where A, B, C and D are fitted parameters and N is the sample size (number of individuals sampled). For crab a slightly different formula was used $(\sigma_{error}^2) = (A * \text{EXP}(B * N) + C)$. The crab formulation was used for scallops as well. Both models involve different parameter sets for different length classes, and achieve very good fits to the error variance values.
 - d) Given the logit transformation, the difficulty is to calculate the value of $\sigma_{i,error,s,p}^2$, the error variance in “untransformed p-space”.
 - e) Let $z_{i,s} = \ln \frac{(p_{i,s} + \delta)}{1 - (p_{i,s} + \delta)}$, where δ is 10% of the stratified mean $\delta = 0.1\bar{p}$.

- f) The variance of $p_{i,s}$, $\sigma_{i,error,s,p}^2$, is obtained by a “logit back-transformation” of $z_{i,s}$ and $\sigma_{i,error,s,z}^2$. A user defined function was written in Excel to carry out these calculations. In initial calculations a thousand values of $z_{i,s}$ were generated with a mean of $z_{i,s} = \ln \frac{(p_{i,s} + \delta)}{1 - (p_{i,s} + \delta)}$, back-transformed with the equation $p_{i,s} = \frac{e^{z_i}}{1 + e^{z_i}}$, and the set of back-transformed values was used to calculate the variance of $p_{i,s}$. It was noted however that the mean of this set of back-transformed values $p_{i,s}$ was not the same as the original value of $p_{i,s}$ values. In order to achieve parity between the original p value and the mean of the set of back-transformed values, an empirically determined adjustment is first applied to the, so that the mean of z in logit space used in the simulations is $z_{i,s} = \ln \frac{(p_{i,s} + \delta)}{1 - (p_{i,s} + \delta)} * adjust$, where adjust is a function of $\sigma_{i,error,s,z}^2$, $adjust = 0.096512139\sigma_{i,error,s,z}^2 + 1.044671586$.
- g) Given the values $p_{i,s}$ and $\sigma_{i,error,s,p}^2$, for all $i \in (1, N_s)$, the stratum means are $\bar{p}_s = \frac{\sum_{i \in (1, N_s)} p_{i,s}}{N_s}$ and the variances of the stratum means are $\sigma_s^2 = \frac{\sum_{i \in (1, N_s)} \sigma_{i,error,s,p}^2}{N_s^2}$, where the subscript p denotes the original proportion domain of the input data, also viewed as the “logit back-transformed” space. (Note: the variance of the stratum means is not based on the cross record variance within a stratum, as would commonly be the case, since we now have access to a variance component model and results which provide direct estimates of the error variance of individual records).
- h) The variance of the stratified mean is $\sigma^2 = \sum_{s \in (1, K)} w_s^2 \sigma_s^2$, where the values of w_s are renormalised such that the summation $\sum_{s \in (1, K)} w_s = 1$ holds for all strata that contain non-zero sampling records.
- i) The variance of the three year average stratified mean (as used in the LCA calculations) is $\sigma^2/3$, the CV of the three year average stratified mean is $CV = 100 \frac{\sqrt{\sigma^2/3}}{\bar{p}}$, and $MWCV = \sum_{l} \bar{p}_l CV$, where the summation is over all length classes relevant for LCA.

10.2.3 Methods - Variance and MWCV of alternative sampling designs

In order to estimate the sampling variance of alternative sampling designs, the calculation approach is very similar to the approach taken in the previous section, where the MWCV for the existing sampling design is estimated for all years 2006 to 2016. The important differences in the approach used here are as follows:

- The number of records per stratum are set a priori (different options are investigated).
- The sample sizes per record are set a prior (different options are investigated).
- The “observed” proportion for each record are the stratum means from the available 2006 to 2016 data. If there are no data available to provide an “observed” proportion for a stratum at the level of month x statistical area, the value used is the average over all available records.

10.3 Results - Variance component estimates

The following variance component estimates are reported here:

- Table 10.1 Variance components estimated via GLMER, for all records except those for Shetland, for lobsters in the length class 95 to 100 cm. The three sets of results

are for all records, and then for two groups of records selected on the basis of the sample size per record.

- Table 10.2 Variance components across all length bins, estimated using GLMER with a binomial distributions and a logit link function, excluding Shetlands, for lobster. Results are shown for all recorded data “All” and in three bins of the number of samples taken per trip. The values shown are in the logit transformed domain and need to be backtransformed to interpret them in relation to actual proportions.
- Table 10.3 Variance components across all length bins, estimated using GLMER with a binomial distributions and a logit link function, excluding Shetlands, for lobster. Results are shown for all recorded data “All” and in five bins of the number of samples taken per trip. The values shown are in the logit transformed domain and need to be backtransformed to be interpreted in relation to catch proportions. Results for sizes above 145 mm are considered to be unreliable.
- Table 10.4 A table showing the values of the variance in a proportion for given values of the logit transformed value and the variance of that value.
- Table 10.5 Variance components lobster for all assessment areas other than Shetland, including in the variance component analysis the statistical area (I) and month (M), as well as year (Y), gender (G), season (S) and assessment area (A). A weighted GLMER model was run.
- Table 10.6 Variance components for crab for all assessment areas other than Shetland, including in the variance component analysis the statistical area (I), month (M), year (Y), gender (G) and assessment area (A). An unweighted GLMER model was run.
- Table 10.7 Variance components lobster for all assessment areas other than Shetland, including in the variance component analysis the year (Y), gender (G) and assessment area (A). Weighted GLMER results
- Table 10.8 Variance components lobster for all assessment areas other than Shetland, including in the variance component analysis the year (Y), gender (G) and assessment area (MA). Unweighted GLMER results.
- Table 10.9 Variance components for crab for all assessment areas other than Shetland, including in the variance component analysis the year (Y), gender (G) and assessment area (MA). Weighted GLMER results.
- Table 10.10 Variance components crab for all assessment areas other than Shetland, including in the variance component analysis the year and assessment area. Unweighted GLMER results.
- Table 10.11 Variance components for scallops for all assessment areas other than the Irish Sea, including in the variance component analysis the statistical area (S), month (M), year (Y) and management area (A). Weighted GLMER results.
- Table 10.12 Variance components for scallops for all assessment other than the Irish Sea, including in the variance component analysis, the year (Y) and assessment area (A). Weighted GLMER results.

10.4 Results - MWCV estimates for existing sampling programmes

MWCV is an abbreviation for the quantity “Mean Weighted Coefficient of Variation”. For a normalised length frequency, i.e. where the proportions of the length frequencies sum up to 1,

the MWCV is the sum of the proportion p for each length class, multiplied by its CV, summed up over all length classes. The following MWCV results are reported here:

- Table 10.13 MWCV estimates for lobster for all areas except Shetland, for the existing sampling regimes 2007 to 2016, for all different ways of calculating the error variance.
- Table 10.14 MWCV estimates for lobster for all areas except Shetland, for the existing sampling regimes 2007 to 2016 continuation of previous table.
- Table 10.15 MWCV estimates for crab for all areas except Shetland, for the existing sampling regimes 2007 to 2016.
- Table 10.16 MWCV estimates for crab for all areas except Shetland, for the existing sampling regimes 2007 to 2016, continuation of previous table.
- Table 10.17 MWCV estimates for scallops for all areas except the Irish Sea, for the existing sampling regimes 2007 to 2016.

The following tables provide a summarised assessment of whether biological sampling has achieved an MWCV threshold of either 20% or 30%.

- Table 10.18 An assessment of whether biological sampling for lobster and crab lengths has attained either a 20% or a 30% MWCV threshold over the last five years.
- Table 10.19 An assessment of whether biological sampling for scallop lengths has attained either a 20% or a 30% MWCV threshold over the last five years.

10.5 Results - Alternative sampling designs

Based on the methods and baseline variance estimates presented in detail above, MWCVs can be calculated for prospective and alternative sampling schemes to those that have been realized in the fishery over the last ten years. In initial calculations the long terms mean length structure was used as the basis for these calculations, for crab, lobster and scallops, i.e. the mean length structure over ten years for each stock, with stock defined as management area and gender combinations. Using a simple random sampling design (we found little difference between simple random sampling and stratified random sampling results for historic data sets), the following results were obtained:

- Table 10.20 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for lobster, using the variance components where month and statistical variance components are calculated in GLMER, and the weighted/unweighted cases where the month and statistical area variance components are not estimated. Simple random sampling assumed. Highlighted regions are judged to be undesirable, i.e. MWCV >30%, based loosely on Technical Appendix 3 results which simulated the link between MWCV and LCA based fishing mortality estimates.
- Table 10.21 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for crab, using the variance components where month and statistical variance components are calculated in GLMER, and the weighted/unweighted cases where the month and statistical area variance components are not estimated. Simple random sampling assumed. Highlighted regions are judged to be undesirable, i.e. MWCV >30%.

- Table 10.22 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for scallops, using the variance components where month and statistical variance components are calculated in GLMER (second panel), and the weighted/unweighted cases where the month and statistical area variance components are not estimated. Simple random sampling assumed. Highlighted regions are judged to be undesirable, i.e. MWCV >30%.

These design based results for lobster and crab are more optimistic (the MWCVs are smaller) than the empirical results based on the historical data set (Table 10.13 - Table 10.17), and further investigations were carried out to determine the reasons for this difference. A significant contributing factor seems to be that the sample sizes, for which means are given, are highly variable. For the entire lobster and crab datasets, the sample sizes for the LCA size range of interest has the distribution shown in Figure 10.1 and Figure 10.3.

Here this distribution is approximated by the exponential distribution, subject to the constraint that the sample size is larger than or equal to 1. A simulation across ~2 500 (lobster) or ~4 500 (crab) realizations (~the number of trips in the available biological sampling dataset for lobster or crab) using the exponential distribution parameter which gives the same mean over large number of simulations as the empirical mean, yields a comparable artificially created histogram, although the empirical variance is larger - Figure 10.2 (lobster) and Figure 10.4 (crab).

Some of the cells in Table 10.20 and Table 10.21 were recalculated using the same mean number of individuals sampled per trip, but allowing for them to be randomly selected from an exponential distribution with the same mean.

For example, the simulated MWCV for the case of 40 individuals sampled per trip, and 20 trips sampled showed an inflation of the MWCV from those in Table 10.20 of roughly 70%, for lobsters. These results have not been comprehensively explored here. The simulations that have been done indicate that the variation in, and hence uncontrollability of, the number of lobsters/crabs over the LCA length range that are sampled per trip can significantly increase the MWCV above a design target based on an idealized sampling situation where lobsters/crabs are sampled in precisely the numbers required (easily doubling it in certain circumstances). There are numerous dimensions to this problem. The causes of this problem need to be properly understood in order to propose solutions. The problem is really when low sample sizes are achieved, because the variance on these sample sets will be much higher than the sample design would have predicted. It may, for example, not be possible to sample a designated number in certain cases because the catch is too small. If sample size is being limited for this reason, then the only remedy is to increase the number of trips that are sampled, which is a very expensive option. A positive feature would be if the sample size is strongly correlated with the trip landing for the species of interest. The data available to this study does not permit this to be tested. On the other hand, if there are other reasons for the occurrence of trips with very low sample size (e.g. too many crab and other species) then these need to be understood and dealt with. In circumstances where the sample size is not controlled it is advised that the sampling design results for lobster be read with an MWCV of >20% being undesirable, and not 30%.

Note that the sample size distribution for scallops is much “healthier” and does not suffer from the plethora of undersampled trips seen for lobsters and crab (see Figure 10.1 and Figure 10.3).

10.6 Summary of results

The following tables are a resource that can be used to determine what sampling effort is required to achieve an MWCV value of 30%, which Technical Appendix suggests is adequate as a single year value to lead to LCA based fishing mortality estimates which have sufficient precision for management purposes.

The variance component estimates show important features relevant to the benefits of improvements to the sampling processes. The first, as one would expect, is that the error variance in the logit domain generally declines as the sample size per trip increases (although there are instances where this pattern is not evident). This suggests that increasing the sample size per trip will reduce the Mean Weighted Coefficient of Variation (MWCVs), a measure which is used to quantify the imprecision of the estimated length frequency distribution. Another feature is that there is frequently a tendency for the error variance to reach an asymptotic minimum value as a function of increasing sample size per trip. This suggests that there is only so much reduction in the MWCV that can be achieved by increasing the sample size per trip, and thereafter further reductions in the MWCV can only be achieved by increasing the number of trips sampled. In other words, there is a trip to trip variance component that cannot be eliminated by within trip sampling innovations. These features, and others, are explored in synthesis material presented further on in this section.

Yet a further feature of the variance component estimates given in Table 10.1 to Table 10.12 is that, in certain cases, there are quantitatively important components of variance due to month and statistical area. Although results are reported here in which the error variances are estimated either with or without the inclusion of month and statistical area as random effects in the Generalized Linear Mixed-Effects Models (GLMER) (the algorithm used for variance component estimation), and associated comparative MWCV results are reported, this should not be regarded as full and complete treatment of the impact of month and statistical area variance in the final MWCVs. The reason for this is that there may be a substantial variance component due to month and statistical area that are not evident in the relative scales of the error variance for GLMER runs carried out with or without these variance components present. For example, if 100 samples are taken in month one and only one sample is taken in month two, the error variance will be little impacted even though the month to month variance is substantial. Furthermore, in principle, variance due to month and statistical area could be eliminated if these variables were used to define strata, and balanced sampling of these strata takes place. This has not been the case, and typically less than 10% of the strata, when such strata are defined as all unique month and statistical area combinations, are sampled in any year. Thus the post-hoc stratification calculations presented here, in which stratum weights are re-normalised to cater for unsampled strata, does not really achieve this elimination of variance. A much fairer, albeit approximate, assessment of the impact of lack of balance in the sampling with respect to these strata is to assume simple random sampling and then to consider the proportion of each stratum which is sampled. Since the variance of the mean under simple random sampling conditions is just the sum of the error

variances per record divided by the square of the sample size (if the error variance per record are the same this reduces to the error variance divided by the sample size), plus the month variance component i.e. we consider here only the month component of variance and not that due to statistical area) multiplied by the sum of the square of the proportions of different months that are sampled:

$$\sigma_s^2 = \frac{\sigma_{error}^2}{N_{trips}} + \sigma_{month}^2 \sum_{\text{month}} p_{month}^2 = \frac{\sigma_{error}^2}{N_{trips}} + \sigma_{month}^2 V \quad (10.1)$$

V has a maximum value of 1 when only one month is sampled, and a minimum value of 1/12 = 0.0833 when all months receive the same amount of sampling, which is only theoretically possible when at least 12 trips are sampled.

A first and coarse assessment of the relevance of the month and statistical area variance components cannot be safely based on comparing the relative scales of the I or S (I and S are different indices used in the report which are both for statistical area) and M (month index) variance components to the error variance components in Table 10.5, Table 10.6 and Table 10.11. This is because, for the same number of lobsters sampled per trip, the contribution of the error variance to the variance of the mean declines in inverse proportion to the number of trips sampled, whereas the contribution of the month variance component cannot decline below the 0.0833 factor. This is of course somewhat approximate since months have been treated as random effects even though there are only 12 month effects, but the basic point holds. Later we attempt to give some indication of how serious this effect may be, but for the moment the calculations proceed ignoring the month and statistical area variance components.

10.7 Discussion of results

Based on the methods and baseline variance estimates presented in detail in Technical Appendix 1, the MWCV (Mean Weighted Coefficient of Variation) can be calculated for prospective and alternative sampling schemes which differ from those that have been realized in the fishery over the last ten years. In initial calculations the long term mean length structure averaged over all assessment areas was used as the basis for these calculations, for crab, lobster and scallops; i.e. the mean length structure over ten years for each stock, with stock defined as stock assessment area and gender combinations. Using a simple random sampling design, Table 10.20, Table 10.21 and Table 10.22 show the MWCVs that are obtained. We found little difference between simple random sampling and stratified random sampling results for historic data sets.

The predicted results for lobster and crab are more optimistic than are the empirical results based on the historical data. That is, their MWCV values are smaller for comparable numbers of trips and number of samples per trip. This is best seen in comparisons between the empirical and design based MWCVs given in Table 10.23 to Table 10.25. Further work was carried out to determine the reasons for this difference. A significant contributing factor seems to be that the actual sample sizes per trip sampled are highly variable in the case of the empirical MWCVs, but are assumed invariant for each of the design based options and MWCVs shown in Table 10.23 to Table 10.25. For the entire lobster and crab datasets, the sample sizes over the range of sizes used in LCA size has the empirical distribution shown by the histograms in Figure 10.1 and Figure 10.3:

Here this distribution is approximated by an exponential distribution, subject to the constraint that the sample size is larger than or equal to one. A simulation across ~2,500 (lobster) or ~4,500 (crab) fishing trip realisations was carried out, where the number refers to the approximate number of trips in the available biological sampling dataset for lobster and crab respectively. Using the exponential distribution, and a parameter which is the empirical mean sample size per trip gives an artificially created histogram which is similar to the empirical histogram (see Figure 10.2, lobster and Figure 10.4, crab).

Selected cells in Table 10.13 to Table 10.17 were recalculated using the same mean number of individuals sampled per trip, but allowing for them to be randomly selected from an exponential distribution with the same mean.

When using variable sample sizes, the MWCV for the case – lobsters, and a variable but average number of 40 individuals sampled per trip, with 20 trips sampled – was 70% larger than the associated MWCV based on an invariant 40 trips sampled per trip for every trip. See Table 10.13, Table 10.14 and Table 10.23. While it has not been possible to comprehensively explore results such as this within this study, the simulations that have been done indicate that the variation in, and hence uncontrollability of, the number of lobsters/crabs over the LCA length range that are sampled per trip can significantly increase the MWCV compared to the MWCV from an idealized sampling situation where lobsters/crabs are sampled in precisely the numbers required. This effect is in certain cases at least a 100% inflation of the MWCV. The MWCV inflation effect is due to the occurrence of low sample sizes, because the variance of these sample sets is much higher than results for sample sets where the sample size is equal to or larger than the mean.

There are numerous dimensions to this issue and the causes of low sample size per trip need to be properly understood before clearly recommending specific remediation. We do not know, for example, whether the occurrence of low sample size is because

- a) Low catches, so even though the entire catch was sampled, sample size is low
- b) Low proportion of the species in catches, and the sample that was drawn contained a small number of the species of interest.

Remediation is different depending on whether (a) or (b) are the factor determining a low sample size:

If (a) then in order to mitigate this problem, consideration of sampling vessels with larger catches must be contemplated.

If (b) then oversampling of species which do not show sufficient sample size in the usual random sample that is drawn is required.

Indeed it may not be possible to sample a designated number in certain cases because the catch is too small. If sample size is being limited for this reason, then the only remedy is to increase the number of trips that are sampled. This is a very expensive option. In circumstances where the sample size per trip cannot be controlled to achieve a design level, it is recommended, particularly for lobsters, that the threshold for MWCV be set at 15%, and not 30%, which assumes that the sample size is controlled. The comparison between the “design” based MWCVs and the empirical MWCVs for crab and scallops shown in Table 10.24 and Table 10.25 is much better than the “agreement” shown for

lobsters in Table 10.23. For scallops it is assumed that this is because the sample size distribution (see Figure 10.5) does not show the same exponential distribution feature evident for lobster and crab (Figure 10.1 and Figure 10.3). The reason why this problem is not a factor for crab is not clear at this stage, although it may be because the number of crabs sampled per trip is quite a bit larger on average than lobsters (compare the lobster sample sizes in Figure 10.1 with those in Figure 10.3). The design vs empirical MWCV differences for crabs (Table 10.24) do seem to be intermediate between scallops (Table 10.25) and lobsters (Table 10.23), consistent with crab sample sizes lying between those for scallops and lobsters as an average.

Table 10.5, Table 10.6 and Table 10.11 show the variance components for lobster, crab and scallops for the case where, in addition to year, assessment area and gender, the month and statistical area variance components have been estimated as well. Including these into the design MWCV calculations is complicated because additivity of variances in the logit domain is not the same as additivity of variances in the p-domain.

Note that we do not address or consider the year, assessment area and gender components of variance in our calculations since all analyses and stock assessments are assumed to be stock specific, and the MWCV calculations are relevant to sampling for a whole year.

It seems from Table 10.5, Table 10.6 and Table 10.11 that the month and statistical variance component is moderate for lobsters, non-existent for crabs (although in view of the results for lobsters and scallops this result is somewhat suspicious), and substantial for scallops. This may be a result of genuinely greater spatial heterogeneity of the length structure of scallops compared to either crab or lobsters, in turn possibly due to the greater mobility of crabs and lobsters relative to scallops.

Superficially then, previous calculations and results which have ignored the role of statistical area and month variance components over and above the error variance (due to trip and sample size) cannot be ignored completely. This topic was discussed in Section 3.1.1. It is important to note the following:

- The aim of the biological sampling programme is to sample the catch and to estimate catch-at-length (and not, for example, the population-at-length).
- Month and Statistical Area based stratification may eliminate much of the variance due to these components of variance. This would not be the case when sampling is not representative of the strata where much of the catch takes place.
- The precise mode of raising length frequency data has a potentially strong bearing on how the variance components enter the MWCV of the resultant length frequency distribution. This information was not available for the purposes of this study but nevertheless the raising approach used does need to be assessed in relation to the findings reported here to determine whether alternative approaches with a lower MWCV are feasible.
- There are certain technical complications which have come about because of the logit transformation used in the GLMER to estimate the variance components. This complicates the determination of the impact of added error variance and is not part of the scope of this study.

In view of the above, we take a somewhat *ad hoc* approach to provide an indication of whether the existence of these variance components leads to different sampling design

recommendations than are evident in the results presented thus far. In order to quantify the impact of these variance components on the MWCV values predicted by the idealised design calculations the following steps have been followed:

- Inspection of the relative variance components and error variances for large sample size in Table 10.5, Table 10.6 and Table 10.11, for lobster, crab and scallops.
- From the above it is concluded that the variance components resulting from the statistical area and month add about 2/3 of the variance per length class which is evident in the large sample size error variances, as a general observation across all length classes. This is a statement relevant to variance in the logit transformed domain.
- Determination of the value of V , the balance factor, is not in the scope of this work. Results are presented for a value of 0.25 for lobster and 0.25 and 0.10 for scallops (given the much larger number of trips sampled for scallops one may expect better balance across levels of area and time components than for lobsters).
- The additional variance implied for the p-domain due to area/time variance components is calculated used a UDF (user defined function) developed in Excel to carry out this transformation.
- The above is added to the variance of the p-domain mean which arises as a result of the error variance addressed and described elsewhere in this document.

The results are shown for lobsters in Table 10.26 and for scallops in Table 10.27.

- For lobsters the effect of including month and statistical area variance components in the design MWCVs is small.
- For scallops the impact of the *ad hoc* adjustment made here represents a major reappraisal of the level of scallop MWCVs, compared to calculations which ignore the variance components due to month and statistical area. The necessity for such a reappraisal does however seem to be consistent with the relatively large value of error variance at large sample size for scallops, and also the relatively large value of the statistical area and month components of variance. These results are of course heavily dependent on the assumptions made to produce the adjustments. If these assumptions are invalid, then the adjusted MWCV results would be misleading. If for example, catch is concentrated in only a few strata in time and space then they would be misleading. Resolution of this issue is a large topic which not within the scope of this document.
- Table 10.13 to Table 10.17 in conjunction with the simulation results presented in Figure 12.1, Figure 12.2, Figure 12.3 and Figure 12.4 of Technical Appendix 3 provides a possible first basis for assessing whether the precision of the biological sampling for length leads to adequate fishing mortality estimate precision derived using LCA method, for crab and lobster. The results in Technical Appendix 3 show that LCA can tolerate considerable imprecision in length composition data (e.g. MWCV's of between 20% and 30%) and still produce fishing mortality estimates that have adequate with a CV of less than, say, 20%. Consequently consideration of the results in Technical Appendix 3 does not require that MWCV's need to be less than 20% or even 30%, since LCA seems able to tolerate larger values. An alternative basis for setting an MWCV threshold would seem to be a general need to ensure that a given level of data quality is being achieved. It is suggested here that this quality threshold be chosen somewhere in the range of MWCV between 20% and 30%. At these thresholds, the overall impression from the results in Table 10.13 to Table 10.17 over the last five

years for crab, lobster and scallop in Scottish inshore fisheries is summarised in Table 10.18 and Table 10.19.

Table 10.1 Variance components estimated via GLMER, for all records except those for Shetland, for lobsters in the length class 95 to 100 cm. The three sets of results are for all records, and then for two groups of records selected on the basis of the sample size per record.

	95 - 100 cm length class, lobsters, excluding Shetland		
	All N	N<=25	N>25
n	2546	2180	366
N_Mean	14.90	7.69	54.42
Statistical Area	0.059	0.055	0.000
Month	0.081	0.080	0.044
Management Area	0.514	0.320	0.743
Year	0.019	0.016	0.000
Season	0.013	0.027	0.000
Gender	0.000	0.000	0.000
Error	2.717	3.089	0.535
Intercept	-0.666	-0.512	-0.795
Total Variance	3.402	3.587	1.322

Table 10.2 Variance components across all length bins, estimated using GLMER with a binomial distributions and a logit link function, excluding Shetlands, for lobster. Results are shown for all recorded data “All” and in three bins of the number of samples taken per trip. The values shown are in the logit transformed domain and need to be backtransformed to interpret them in relation to actual proportions.

n	Length	N_Bin	Variance components												
			Mean N Fish sampled	Actual Mean of P	Actual Total Variance of P	Statistical Rectangle	Month	Management Area	Year	Season	Sex	Error	Intercept	Var(Int)	
2546	PAL095	All	14.405	0.39631	0.08620	0.235	0.093	0.327	0.019	0.000	0.005	2.548	-0.902	0.054	
1574		00 - 10	4.412	0.40262	0.11136	0.100	0.055	0.018	0.114	0.014	0.000	3.670	-0.353	0.034	
606		11 - 25	16.196	0.41742	0.04768	0.272	0.169	0.172	0.031	0.000	0.006	0.570	-0.645	0.052	
366	PAL100	>25	54.415	0.33421	0.03731	0.372	0.293	0.464	0.029	0.000	0.008	0.387	-1.138	0.095	
2546		All	14.405	0.19910	0.03976	0.023	0.015	0.000	0.006	0.000	0.014	2.617	-1.450	0.010	
1574		00 - 10	4.412	0.19472	0.05744	0.000	0.004	0.007	0.002	0.004	0.020	3.791	-1.328	0.014	
606	PAL105	11 - 25	16.196	0.20817	0.01361	0.004	0.000	0.004	0.000	0.008	0.006	0.643	-1.393	0.007	
366		>25	54.415	0.20296	0.00692	0.044	0.069	0.000	0.014	0.000	0.016	0.224	-1.557	0.018	
2546		All	14.405	0.12152	0.02552	0.023	0.005	0.036	0.009	0.002	0.001	2.790	-1.797	0.008	
1574	PAL110	00 - 10	4.412	0.11308	0.03597	0.041	0.017	0.000	0.000	0.000	0.000	3.715	-1.937	0.006	
606		11 - 25	16.196	0.13174	0.01037	0.076	0.005	0.024	0.003	0.000	0.002	1.126	-1.794	0.010	
366		>25	54.415	0.14095	0.00490	0.063	0.068	0.007	0.022	0.000	0.001	0.382	-1.794	0.013	
2546	PAL115	All	14.405	0.08283	0.01965	0.083	0.023	0.089	0.012	0.014	0.001	2.902	-2.215	0.021	
1574		00 - 10	4.412	0.07727	0.02783	0.019	0.020	0.000	0.111	0.011	0.000	3.603	-2.521	0.028	
606		11 - 25	16.196	0.08473	0.00750	0.151	0.036	0.001	0.010	0.000	0.000	1.657	-2.372	0.013	
366	PAL120	>25	54.415	0.10361	0.00409	0.096	0.063	0.129	0.020	0.025	0.001	0.549	-2.159	0.035	
2546		All	14.405	0.05144	0.01047	0.141	0.028	0.185	0.028	0.007	0.002	2.637	-2.583	0.035	
1574		00 - 10	4.412	0.04545	0.01407	0.000	0.007	0.069	0.183	0.046	0.000	2.839	-2.960	0.056	
606	PAL125	11 - 25	16.196	0.05362	0.00509	0.283	0.053	0.095	0.047	0.000	0.003	2.053	-2.827	0.039	
366		>25	54.415	0.07360	0.00329	0.179	0.060	0.171	0.030	0.000	0.002	0.793	-2.405	0.038	
2546		All	14.405	0.04030	0.00952	0.191	0.057	0.337	0.011	0.021	0.018	2.601	-2.859	0.065	
1574	PAL130	00 - 10	4.412	0.03873	0.01343	0.001	0.065	0.117	0.356	0.009	0.005	2.790	-3.426	0.091	
606		11 - 25	16.196	0.03567	0.00327	0.133	0.083	0.350	0.068	0.033	0.022	2.252	-3.198	0.089	
366		>25	54.415	0.05469	0.00280	0.259	0.088	0.241	0.000	0.031	0.014	1.014	-2.710	0.063	
2546	PAL135	All	14.405	0.02482	0.00459	0.306	0.039	0.159	0.024	0.000	0.051	2.368	-3.453	0.063	
1574		00 - 10	4.412	0.02160	0.00620	0.169	0.049	0.195	0.479	0.043	0.036	2.181	-3.934	0.157	
606		11 - 25	16.196	0.02654	0.00211	0.094	0.038	0.307	0.035	0.039	0.046	2.330	-3.553	0.092	
366	PAL140	>25	54.415	0.03582	0.00164	0.327	0.043	0.121	0.050	0.000	0.050	1.374	-3.289	0.064	
2546		All	14.405	0.02002	0.00599	0.410	0.108	0.115	0.038	0.000	0.075	2.314	-3.881	0.082	
1574		00 - 10	4.412	0.02127	0.00899	0.257	0.008	0.056	0.049	0.000	0.089	2.233	-4.202	0.092	
606	PAL145	11 - 25	16.196	0.01583	0.00122	0.016	0.180	0.378	0.084	0.000	0.067	2.239	-4.044	0.122	
366		>25	54.415	0.02160	0.00093	0.901	0.069	0.061	0.000	0.000	0.066	1.607	-3.821	0.083	
2546		All	14.405	0.01036	0.00303	0.587	0.026	0.105	0.041	0.026	0.081	1.915	-4.404	0.092	
1574	PAL150	00 - 10	4.412	0.00993	0.00449	0.000	0.027	0.000	0.516	0.019	0.079	1.565	-4.853	0.169	
606		11 - 25	16.196	0.00935	0.00077	0.322	0.009	0.564	0.000	0.052	0.115	1.970	-4.828	0.190	
366		>25	54.415	0.01391	0.00047	0.498	0.237	0.000	0.047	0.000	0.068	1.911	-4.166	0.088	
2546	PAL155	All	14.405	0.00678	0.00163	0.392	0.110	0.000	0.026	0.000	0.138	1.628	-4.997	0.103	
1574		00 - 10	4.412	0.00665	0.00234	0.068	0.243	0.022	0.180	0.000	0.195	1.202	-5.320	0.204	
606		11 - 25	16.196	0.00593	0.00053	0.000	0.042	0.161	0.194	0.290	0.280	1.689	-5.483	0.301	
366	PAL160	>25	54.415	0.00872	0.00035	0.752	0.045	0.036	0.000	0.000	0.093	2.137	-4.841	0.097	
2546		All	14.405	0.00371	0.00059	0.894	0.105	0.000	0.045	0.000	0.214	1.410	-5.372	0.163	
1574		00 - 10	4.412	0.00238	0.00073	0.527	0.000	0.011	0.000	0.000	0.000	0.611	-6.029	0.116	
606	PAL165	11 - 25	16.196	0.00599	0.00048	0.519	0.000	0.027	0.145	0.000	0.442	1.703	-5.378	0.297	
366		>25	54.415	0.00566	0.00018	0.724	0.186	0.000	0.082	0.000	0.162	1.922	-5.269	0.156	
2546		All	14.405	0.00213	0.00049	0.756	0.000	0.000	0.000	0.036	0.408	1.165	-6.406	0.269	
1574	PAL170	00 - 10	4.412	0.00225	0.00074	0.002	0.000	0.000	0.000	0.000	0.104	0.486	-6.156	0.120	
606		11 - 25	16.196	0.00143	0.00010	0.939	0.000	0.000	0.000	0.783	0.189	1.142	-6.629	0.449	
366		>25	54.415	0.00273	0.00008	0.743	0.000	0.000	0.000	0.000	0.482	1.739	-6.273	0.312	
2546	PAL175	All	14.405	0.00143	0.00056	1.014	0.607	0.000	0.000	0.214	0.732	1.143	-6.958	0.567	
1574		00 - 10	4.412	0.00146	0.00085	0.000	4.931	2.400	0.000	0.000	0.987	1.598	-8.424	1.768	
606		11 - 25	16.196	0.00163	0.00014	0.294	0.363	0.000	0.338	0.264	2.008	1.535	-6.821	1.331	
366	PAL180	>25	54.415	0.00092	0.00002	2.095	0.000	0.000	0.034	0.015	0.225	1.250	-6.946	0.283	
2546		All	14.405	0.00066	0.00017	1.653	0.667	0.591	0.493	0.000	0.821	0.952	-7.977	0.807	
1574		00 - 10	4.412	0.00064	0.00020	0.000	0.000	0.000	1.856	0.000	0.119	0.481	-6.832	0.623	
606	PAL185	11 - 25	16.196	0.00079	0.00019	24.263	0.000	0.000	7.178	0.000	3.752	0.505	-10.212	6.222	
366		>25	54.415	0.00051	0.00002	0.000	0.000	0.000	0.162	0.000	0.000	0.181	-9.890	1.020	
2546		All	14.405	0.00002	0.00004	0.803	0.000	0.000	0.000	2.497	0.000	0.373	-10.282	1.723	
1574	PAL190	00 - 10	4.412	0.00003	0.00000	-	-	-	-	-	-	-	-	-	
606		11 - 25	16.196	0.00000	0.00000	0.000	0.000	0.000	0.000	0.000	0.000	0.127	-9.192	1.000	
366		>25	54.415	0.00002	0.00000	0.000	0.000	0.000	0.000	0.000	0.000	0.184	-9.899	1.000	
2546	PAL195	All	14.405	0.00004	0.00000	-	-	-	-	-	-	-	-	-	
1574		00 - 10	4.412	0.00000	0.00000	-	-	-	-	-	-	-	-	-	
606		11 - 25	16.196	0.00001	0.00001	0.417	0.000	0.000	0.702	2.077	0.000	0.290	-8.983	1.670	
366	PAL199	>25	54.415	0.00000	0.00000	-	-	-	-	-	-	-	-	-	
2546		All	14.405	0.00003	0.00000	1.914	0.000	0.000	0.087	2.267	0.000	0.331	-10.264	1.751	
1574		00 - 10	4.412	0.00000	0.00000	-	-	-	-	-	-	-	-	-	
606	PAL200	11 - 25	16.196	0.00008	0.00000	1.858	0.000	0.000	0.000	2.009	0.000	0.296	-8.987	1.626	

Table 10.3 Variance components across all length bins, estimated using GLMER with a binomial distributions and a logit link function, excluding Shetlands, for lobster. Results are shown for all recorded data “All” and in five bins of the number of samples taken per trip. The values shown are in the logit transformed domain and need to be backtransformed to be interpreted in relation to catch proportions. Results for sizes above 145 mm are considered to be unreliable.

Record Count	Length Class	N_Bin	Model Input		Actuals			Variance components						Residuals	Fixed Effects	
			Mean NAL	Mean N Sex_ Int	Mean PAL	Actual Variance	VarCom p_SR	VarCom p_M	VarCom p_MA	VarCom p_Y	VarCom p_S	VarCom p_G	Error variance	Intercept	Var(Int)	
1033	PAL095	5-	1.1	2.6	0.387	0.139	0.092	0.051	0.172	0.045	0.041	0.004	5.025	-0.229	0.060	
		5 -15	4.1	9.6	0.429	0.056	0.214	0.079	0.065	0.024	0.000	0.001	0.968	-0.530	0.028	
		15 - 25	8.0	19.8	0.410	0.044	0.268	0.199	0.034	0.144	0.000	0.003	0.448	-0.677	0.053	
		25 - 40	11.8	31.6	0.372	0.041	0.155	0.340	0.631	0.023	0.000	0.007	0.311	-1.159	0.117	
		40+	21.8	72.8	0.304	0.032	0.675	1.808	0.199	0.090	0.000	0.009	0.282	-1.354	0.218	
847	PAL100	5-	0.5	2.6	0.185	0.075	0.020	0.000	0.000	0.007	0.021	0.021	4.912	-1.344	0.017	
		5 -15	2.0	9.6	0.210	0.021	0.003	0.004	0.002	0.000	0.008	0.012	1.194	-1.368	0.010	
		15 - 25	4.2	19.8	0.211	0.012	0.003	0.000	0.004	0.007	0.002	0.004	0.531	-1.369	0.006	
		25 - 40	6.8	31.6	0.217	0.009	0.042	0.016	0.014	0.001	0.000	0.010	0.276	-1.386	0.013	
		40+	13.8	72.8	0.192	0.005	0.038	0.189	0.000	0.017	0.000	0.020	0.139	-1.648	0.032	
300	PAL105	5-	0.3	2.6	0.106	0.046	0.000	0.025	0.085	0.010	0.000	0.000	4.361	-2.154	0.026	
		5 -15	1.2	9.6	0.127	0.014	0.006	0.016	0.036	0.000	0.000	0.001	1.878	-1.893	0.010	
		15 - 25	2.7	19.8	0.134	0.009	0.086	0.000	0.011	0.019	0.004	0.000	0.876	-1.744	0.011	
		25 - 40	4.5	31.6	0.142	0.006	0.019	0.035	0.030	0.012	0.000	0.000	0.500	-1.702	0.013	
		40+	10.3	72.8	0.140	0.004	0.010	0.124	0.038	0.064	0.000	0.000	0.235	-1.928	0.025	
163	PAL110	5-	0.2	2.6	0.078	0.037	0.057	0.000	0.098	0.000	0.013	0.000	4.011	-2.496	0.035	
		5 -15	0.8	9.6	0.079	0.010	0.132	0.040	0.021	0.006	0.007	0.001	2.319	-2.376	0.019	
		15 - 25	1.7	19.8	0.083	0.007	0.034	0.050	0.029	0.188	0.000	0.000	1.433	-2.370	0.038	
		25 - 40	2.9	31.6	0.091	0.005	0.210	0.043	0.102	0.014	0.000	0.000	0.792	-2.385	0.034	
		40+	8.4	72.8	0.113	0.003	0.062	0.144	0.137	0.025	0.000	0.000	0.295	-2.088	0.038	
203	PAL115	5-	0.1	2.6	0.042	0.018	0.281	0.000	0.187	0.194	0.109	0.069	2.688	-3.247	0.155	
		5 -15	0.5	9.6	0.052	0.006	0.087	0.017	0.109	0.031	0.026	0.000	2.552	-2.766	0.036	
		15 - 25	1.1	19.8	0.055	0.004	0.279	0.030	0.064	0.120	0.000	0.010	1.660	-2.886	0.049	
		25 - 40	1.9	31.6	0.060	0.004	0.000	0.241	0.353	0.015	0.000	0.022	1.141	-2.370	0.085	
		40+	6.1	72.8	0.084	0.003	0.236	0.093	0.085	0.052	0.000	0.000	0.444	-2.366	0.038	
847	PAL120	5-	0.1	2.6	0.039	0.018	0.000	0.000	0.287	0.152	0.082	0.005	2.819	-3.294	0.113	
		5 -15	0.3	9.6	0.037	0.005	0.021	0.062	0.229	0.055	0.000	0.000	2.534	-3.282	0.053	
		15 - 25	1.7	19.8	0.038	0.003	0.215	0.038	0.084	0.382	0.024	0.043	1.904	-3.205	0.108	
		25 - 40	2.9	31.6	0.045	0.003	0.084	0.022	0.717	0.000	0.045	0.011	1.506	-2.750	0.113	
		40+	4.6	72.8	0.062	0.003	0.367	0.107	0.048	0.000	0.012	0.012	0.581	-2.692	0.044	
163	PAL125	5-	0.1	2.6	0.029	0.008	0.076	0.099	0.448	0.025	0.084	0.067	2.017	-3.906	0.192	
		5 -15	0.2	9.6	0.025	0.003	0.061	0.078	0.587	0.047	0.062	0.030	2.274	-3.759	0.139	
		15 - 25	0.5	19.8	0.028	0.002	0.014	0.081	0.044	0.363	0.000	0.054	2.253	-3.462	0.098	
		25 - 40	0.9	31.6	0.028	0.001	0.000	0.116	0.353	0.000	0.000	0.071	1.942	-3.428	0.106	
		40+	3.1	72.8	0.042	0.002	0.374	0.064	0.039	0.140	0.000	0.048	0.940	-3.128	0.070	
203	PAL130	5-	0.1	2.6	0.024	0.012	0.480	0.000	0.000	0.088	0.000	0.000	2.327	-4.007	0.072	
		5 -15	0.2	9.6	0.016	0.002	0.042	0.089	0.244	0.000	0.021	0.196	2.150	-4.193	0.167	
		15 - 25	0.3	19.8	0.016	0.001	0.119	0.120	0.074	0.220	0.000	0.031	2.208	-4.028	0.089	
		25 - 40	0.5	31.6	0.017	0.001	0.000	0.000	1.583	0.000	0.094	0.036	1.939	-3.840	0.248	
		40+	1.9	72.8	0.025	0.001	0.455	0.067	0.000	0.000	0.000	0.071	1.374	-3.652	0.067	
847	PAL135	5-	0.0	2.6	0.011	0.006	0.000	0.000	0.528	0.000	0.082	0.073	1.529	-4.824	0.233	
		5 -15	0.1	9.6	0.009	0.001	0.080	0.000	0.420	0.000	0.000	0.112	1.706	-4.860	0.154	
		15 - 25	0.2	19.8	0.010	0.001	0.150	0.103	0.000	0.398	0.000	0.073	2.020	-4.667	0.143	
		25 - 40	0.4	31.6	0.012	0.000	0.295	0.098	0.281	0.000	0.000	0.124	2.063	-4.518	0.095	
		40+	1.2	72.8	0.016	0.000	0.474	0.246	0.000	0.129	0.000	0.082	1.587	-4.050	0.109	
163	PAL140	5-	0.0	2.6	0.007	0.003	0.000	0.000	0.367	1.414	0.000	0.000	1.390	-5.450	0.550	
		5 -15	0.1	9.6	0.007	0.001	0.036	0.054	0.300	0.063	0.277	0.462	1.577	-5.508	0.414	
		15 - 25	0.1	19.8	0.005	0.000	0.000	0.000	0.134	0.000	0.000	0.000	1.753	-5.414	0.054	
		25 - 40	0.2	31.6	0.007	0.000	0.297	0.148	0.467	0.278	0.000	0.124	1.902	-5.171	0.253	
		40+	0.8	72.8	0.010	0.000	0.654	0.098	0.000	0.000	0.000	0.078	1.998	-4.667	0.092	
203	PAL145	5-	0.0	2.6	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.399	-5.954	0.143	
		5 -15	0.0	9.6	0.004	0.000	0.488	0.383	0.000	0.068	0.047	0.350	1.232	-5.449	0.305	
		15 - 25	0.1	19.8	0.006	0.000	0.248	0.199	0.173	0.000	0.000	0.408	1.651	-5.351	0.303	
		25 - 40	0.1	31.6	0.005	0.000	0.687	0.000	0.173	0.096	0.000	0.016	1.676	-5.421	0.139	
		40+	0.5	72.8	0.006	0.000	0.444	0.165	0.000	0.211	0.000	0.194	1.983	-5.104	0.180	

Table 10.4 A table showing the values of the variance in a proportion for given values of the logit transformed value and the variance of that value.

		Mean value of z																					
		-2.00	-1.80	-1.60	-1.40	-1.20	-1.00	-0.80	-0.60	-0.40	-0.20	0.00	0.20	0.40	0.60	0.80	1.00	1.20	1.40	1.60	1.80	2.00	
Variance of z	0.1	0.0012	0.0018	0.0020	0.0026	0.0033	0.0039	0.0044	0.0050	0.0055	0.0058	0.0061	0.0058	0.0056	0.0051	0.0045	0.0039	0.0032	0.0025	0.0020	0.0015	0.0012	
	0.5	0.0067	0.0090	0.0105	0.0136	0.0156	0.0181	0.0203	0.0229	0.0240	0.0252	0.0252	0.0248	0.0239	0.0223	0.0201	0.0179	0.0152	0.0129	0.0110	0.0089	0.0070	
	0.9	0.0139	0.0163	0.0200	0.0242	0.0269	0.0308	0.0341	0.0365	0.0384	0.0395	0.0394	0.0400	0.0393	0.0361	0.0334	0.0296	0.0266	0.0236	0.0202	0.0168	0.0131	
	1.3	0.0211	0.0241	0.0290	0.0336	0.0370	0.0399	0.0450	0.0467	0.0496	0.0518	0.0516	0.0523	0.0498	0.0475	0.0451	0.0409	0.0363	0.0339	0.0290	0.0247	0.0209	
	1.7	0.0284	0.0322	0.0377	0.0419	0.0455	0.0499	0.0539	0.0578	0.0602	0.0619	0.0623	0.0610	0.0599	0.0571	0.0542	0.0501	0.0452	0.0417	0.0362	0.0326	0.0279	
	2.1	0.0347	0.0390	0.0449	0.0506	0.0541	0.0582	0.0621	0.0656	0.0690	0.0698	0.0706	0.0691	0.0672	0.0659	0.0624	0.0585	0.0547	0.0483	0.0439	0.0401	0.0346	
	2.5	0.0400	0.0455	0.0532	0.0564	0.0616	0.0659	0.0698	0.0738	0.0759	0.0766	0.0785	0.0764	0.0751	0.0745	0.0705	0.0665	0.0626	0.0546	0.0514	0.0465	0.0409	
	2.9	0.0470	0.0530	0.0585	0.0623	0.0696	0.0739	0.0766	0.0802	0.0828	0.0839	0.0838	0.0840	0.0828	0.0802	0.0774	0.0736	0.0683	0.0630	0.0583	0.0524	0.0472	
	3.3	0.0544	0.0581	0.0640	0.0681	0.0726	0.0791	0.0825	0.0854	0.0876	0.0908	0.0905	0.0894	0.0882	0.0852	0.0826	0.0795	0.0748	0.0693	0.0640	0.0575	0.0515	
	3.7	0.0592	0.0641	0.0693	0.0755	0.0778	0.0853	0.0870	0.0909	0.0929	0.0950	0.0947	0.0945	0.0936	0.0903	0.0886	0.0850	0.0790	0.0739	0.0687	0.0629	0.0589	
	4.1	0.0638	0.0688	0.0746	0.0788	0.0845	0.0891	0.0942	0.0954	0.0959	0.0986	0.1004	0.0986	0.0990	0.0945	0.0926	0.0869	0.0846	0.0796	0.0748	0.0686	0.0631	
	4.5	0.0678	0.0712	0.0789	0.0851	0.0900	0.0928	0.0975	0.1001	0.1030	0.1035	0.1037	0.1044	0.1023	0.1004	0.0984	0.0946	0.0887	0.0849	0.0797	0.0742	0.0678	
	4.9	0.0721	0.0779	0.0831	0.0907	0.0922	0.0967	0.1016	0.1044	0.1056	0.1070	0.1094	0.1059	0.1048	0.1043	0.0996	0.0954	0.0940	0.0878	0.0840	0.0779	0.0744	
	5.3	0.0771	0.0816	0.0869	0.0916	0.0993	0.1010	0.1047	0.1091	0.1094	0.1097	0.1106	0.1112	0.1094	0.1074	0.1033	0.1003	0.0969	0.0926	0.0868	0.0821	0.0776	

Table 10.5 Variance components lobster for all assessment areas other than Shetland, including in the variance component analysis the statistical area (I) and month (M), as well as year (Y), gender (G), season (S) and assessment area (A). A weighted GLMER model was run.

Weighted Glmer(AGYMIS) Results for Other Areas Lobster																
Model Input			Actuals				Variance components						Residuals		Fixed Effects	
Length	RC	N_Bin	Mean NAL	Mean N_Sex_Int	Actual Mean PAL	Actual Variance PAL	VarComp I	VarComp M	VarComp A	VarComp Y	VarComp S	VarComp G	VarError Logit	Intercept	Var(Int)	
PAL095	1033	5-	1,132	2,619	0,38729	0,13867	0,09223	0,05126	0,17195	0,04514	0,04132	0,00369	5,02459	-0,22948	0,05995	
	847	5 - 15	4,112	9,594	0,42939	0,05574	0,21449	0,07857	0,06453	0,02381	0,00000	0,00091	0,96804	-0,52989	0,02794	
	300	15 - 25	8,047	19,763	0,40977	0,04353	0,26809	0,19942	0,03419	0,14357	0,00000	0,00318	0,44810	-0,67680	0,05313	
	163	25 - 40	11,767	31,558	0,37226	0,04125	0,15503	0,34018	0,63090	0,02313	0,00000	0,00659	0,31074	-1,15920	0,11744	
	203	40+	21,754	72,768	0,30366	0,03223	0,67547	1,80834	0,19856	0,09045	0,00000	0,00879	0,28182	-1,35409	0,21805	
PAL100	1033	5-	0,529	2,619	0,18514	0,07479	0,01985	0,00000	0,00000	0,00000	0,00693	0,02090	4,91222	-1,34399	0,01676	
	847	5 - 15	2,015	9,594	0,21037	0,02087	0,00272	0,00436	0,00242	0,00000	0,00776	0,01221	1,19406	-1,36786	0,01025	
	300	15 - 25	4,167	19,763	0,21065	0,01165	0,00330	0,00000	0,00353	0,00709	0,00217	0,00374	0,53101	-1,36911	0,00566	
	163	25 - 40	6,804	31,558	0,21713	0,00857	0,04181	0,01594	0,01397	0,00147	0,00000	0,00979	0,27580	-1,38564	0,01286	
	203	40+	13,754	72,768	0,19159	0,00533	0,03847	0,18860	0,00000	0,01659	0,00000	0,02025	0,13946	-1,64814	0,03176	
PAL105	1033	5-	0,305	2,619	0,10610	0,04636	0,00000	0,02514	0,08470	0,01031	0,00000	0,00000	4,36137	-2,15437	0,02630	
	847	5 - 15	1,220	9,594	0,12749	0,01443	0,00611	0,01589	0,03644	0,00000	0,00000	0,00127	1,87770	-1,89322	0,01002	
	300	15 - 25	2,653	19,763	0,13409	0,00889	0,08620	0,00000	0,01050	0,01861	0,00447	0,00014	0,87616	-1,74362	0,01094	
	163	25 - 40	4,460	31,558	0,14164	0,00636	0,01869	0,03504	0,02979	0,01235	0,00000	0,00000	0,50050	-1,70178	0,01317	
	203	40+	10,305	72,768	0,14039	0,00376	0,00982	0,12395	0,03838	0,06430	0,00000	0,00043	0,23502	-1,92751	0,02537	
PAL110	1033	5-	0,215	2,619	0,07833	0,03672	0,05693	0,00000	0,09825	0,00000	0,01284	0,00000	4,01107	-2,49554	0,03510	
	847	5 - 15	0,774	9,594	0,07926	0,00990	0,13164	0,03963	0,02131	0,00623	0,00740	0,00088	2,31872	-2,37648	0,01890	
	300	15 - 25	1,667	19,763	0,08307	0,00691	0,03402	0,05004	0,02871	0,18751	0,00000	0,00000	1,43342	-2,36966	0,03775	
	163	25 - 40	2,902	31,558	0,09135	0,00468	0,21032	0,04306	0,10161	0,01350	0,00000	0,00000	0,79244	-2,38462	0,03405	
	203	40+	8,424	72,768	0,11346	0,00342	0,06223	0,14384	0,13675	0,02513	0,00000	0,00012	0,29487	-2,08838	0,03820	
PAL115	1033	5-	0,132	2,619	0,04230	0,01799	0,28079	0,00000	0,18722	0,19437	0,10946	0,06868	2,68797	-3,24668	0,15491	
	847	5 - 15	0,499	9,594	0,05169	0,00634	0,08678	0,01720	0,10928	0,03098	0,02635	0,00000	2,55228	-2,76571	0,03621	
	300	15 - 25	1,100	19,763	0,05518	0,00418	0,27867	0,03006	0,06392	0,12019	0,00000	0,00968	1,66005	-2,88565	0,04895	
	163	25 - 40	1,933	31,558	0,06033	0,00351	0,00000	0,24145	0,35312	0,01489	0,00000	0,02221	1,14080	-2,36983	0,08460	
	203	40+	6,118	72,768	0,08425	0,00287	0,23603	0,09347	0,08455	0,05185	0,00000	0,00000	0,44419	-2,36620	0,03780	
PAL120	1033	5-	0,114	2,619	0,03888	0,01776	0,00000	0,00000	0,28742	0,15185	0,08221	0,00452	2,81919	-3,29385	0,11341	
	847	5 - 15	0,341	9,594	0,03652	0,00462	0,02145	0,06206	0,22885	0,05523	0,00000	0,00000	2,53380	-3,28213	0,05285	
	300	15 - 25	0,760	19,763	0,03827	0,00292	0,21495	0,03836	0,08368	0,38243	0,02415	0,04311	1,90447	-3,20493	0,10811	
	163	25 - 40	1,423	31,558	0,04517	0,00296	0,08405	0,02153	0,71686	0,00000	0,04509	0,01094	1,50606	-2,75018	0,11300	
	203	40+	4,601	72,768	0,06233	0,00256	0,36680	0,10748	0,04779	0,00000	0,01166	0,01236	0,58079	-2,69239	0,04358	
PAL125	1033	5-	0,066	2,619	0,02001	0,00765	0,07567	0,09886	0,44759	0,02505	0,08450	0,06668	2,01745	-3,90629	0,19207	
	847	5 - 15	0,235	9,594	0,02486	0,00301	0,06119	0,07833	0,58697	0,04700	0,06241	0,02979	2,27438	-3,75864	0,13922	
	300	15 - 25	0,547	19,763	0,02784	0,00194	0,01362	0,08068	0,04412	0,36300	0,00000	0,05445	2,25305	-3,46169	0,09843	
	163	25 - 40	0,902	31,558	0,02819	0,00133	0,00000	0,11641	0,35334	0,00000	0,07146	0,194180	-3,42763	0,10615		
	203	40+	3,074	72,768	0,04194	0,00181	0,37372	0,06435	0,03947	0,14033	0,00000	0,04842	0,93997	-3,12829	0,07012	
PAL130	1033	5-	0,064	2,619	0,02372	0,01240	0,47969	0,00000	0,00000	0,08752	0,00000	0,00000	2,32707	-4,00715	0,07156	
	847	5 - 15	0,158	9,594	0,01641	0,00211	0,04165	0,08930	0,24354	0,00000	0,02059	0,19577	2,15012	-4,19263	0,16722	
	300	15 - 25	0,317	19,763	0,01558	0,00093	0,11884	0,12045	0,07379	0,22030	0,00000	0,03072	2,20794	-4,02829	0,08927	
	163	25 - 40	0,540	31,558	0,01730	0,00098	0,00000	0,158335	0,00000	0,09427	0,03636	1,93943	-3,83991	0,24840		
	203	40+	1,857	72,768	0,02505	0,00088	0,45535	0,06675	0,00000	0,00000	0,07058	1,37363	-3,65240	0,06662		

Table 10.6 Variance components for crab for all assessment areas other than Shetland, including in the variance component analysis the statistical area (I), month (M), year (Y), gender (G) and assessment area (A). An unweighted GLMER model was run.

Unweighted Glmer(AGYMI) Results for Other Areas Crab																
Model Input			Actuals				Variance components						Residuals	Fixed Effects		
Length Bin	RC	N_Bin	Mean NAL	Mean N_Bin	Actual Mean PAL	Actual PAL Variance	VarComp I	VarComp M	VarComp A	VarComp Y	VarComp G	VarError Logit	Intercept	Var Intercept		
PAL145	1701	00 - 30	2,464	12,987	0,18858	0,04714	0,00000	0,10723	0,00000	0,00000	0,00000	2,96060	-1,43080	0,01409		
	956	31 - 60	7,785	44,262	0,17611	0,01565	0,00000	0,00000	0,00000	0,00000	0,00000	1,23100	-1,54295	0,00721		
	756	61 - 100	12,927	78,930	0,16499	0,01185	0,00000	0,00000	0,00000	0,00000	0,00000	1,02240	-1,62153	0,00958		
	612	100 - 200	19,332	139,475	0,14153	0,01035	0,00000	0,00000	0,00000	0,00000	0,00000	1,12106	-1,80264	0,01345		
	404	>200	27,542	484,252	0,07461	0,00611	0,00000	0,00000	0,00000	0,00000	0,00000	1,23960	-2,51795	0,03585		
PAL150	1701	00 - 30	2,469	12,987	0,19067	0,03521	0,00000	0,00000	0,00000	0,00000	0,00000	2,41882	-1,44569	0,00381		
	956	31 - 60	8,164	44,262	0,18509	0,00849	0,00000	0,00000	0,00000	0,00000	0,00000	0,52699	-1,48226	0,00694		
	756	61 - 100	13,908	78,930	0,17747	0,00619	0,00000	0,00000	0,00000	0,00000	0,00000	0,41619	-1,53359	0,00904		
	612	100 - 200	22,114	139,475	0,16030	0,00536	0,00000	0,00000	0,00000	0,00000	0,00000	0,41531	-1,65600	0,01214		
	404	>200	52,455	484,252	0,12077	0,00425	0,00000	0,00000	0,00000	0,00000	0,00000	0,41399	-1,98518	0,02331		
PAL155	1701	00 - 30	2,110	12,987	0,15992	0,02652	0,00000	0,00000	0,00000	0,00000	0,00000	2,26206	-1,65880	0,00438		
	956	31 - 60	7,190	44,262	0,16231	0,00447	0,00000	0,00000	0,00000	0,00000	0,00000	0,31200	-1,64117	0,00769		
	756	61 - 100	12,840	78,930	0,16297	0,00282	0,00000	0,00000	0,00000	0,00000	0,00000	0,17248	-1,63631	0,00967		
	612	100 - 200	21,592	139,475	0,15575	0,00242	0,00000	0,00000	0,00000	0,00000	0,00000	0,16175	-1,69019	0,01243		
	404	>200	68,062	484,252	0,14295	0,00189	0,00000	0,00000	0,00000	0,00000	0,00000	0,13147	-1,79096	0,02020		
PAL160	1701	00 - 30	1,867	12,987	0,14034	0,02508	0,00000	0,00000	0,00000	0,00000	0,00000	2,44482	-1,81251	0,00487		
	956	31 - 60	6,223	44,262	0,14025	0,00405	0,00000	0,00000	0,00000	0,00000	0,00000	0,33361	-1,81318	0,00867		
	756	61 - 100	11,443	78,930	0,14514	0,00280	0,00000	0,00000	0,00000	0,00000	0,00000	0,18038	-1,77322	0,01063		
	612	100 - 200	20,466	139,475	0,14691	0,00189	0,00000	0,00000	0,00000	0,00000	0,00000	0,12478	-1,75908	0,01304		
	404	>200	77,181	484,252	0,15520	0,00122	0,00000	0,00000	0,00000	0,00000	0,00000	0,06791	-1,69442	0,01888		
PAL165	1701	00 - 30	1,327	12,987	0,10153	0,02113	0,00000	0,00000	0,00000	0,00000	0,00000	2,80938	-2,18566	0,00963		
	956	31 - 60	4,877	44,262	0,11040	0,00370	0,00000	0,00000	0,00000	0,00000	0,00000	0,48624	-2,08671	0,01065		
	756	61 - 100	8,743	78,930	0,11035	0,00257	0,00000	0,00000	0,00000	0,00000	0,00000	0,28670	-2,08722	0,01344		
	612	100 - 200	16,382	139,475	0,11658	0,00195	0,00000	0,00000	0,00000	0,00000	0,00000	0,18655	-2,02522	0,01586		
	404	>200	71,993	484,252	0,14112	0,00137	0,00000	0,00000	0,00000	0,00000	0,00000	0,09888	-1,80604	0,02042		
PAL170	1701	00 - 30	0,961	12,987	0,07149	0,01332	0,00000	0,00000	0,00000	0,00000	0,00000	2,70022	-2,56406	0,00886		
	956	31 - 60	3,697	44,262	0,08299	0,00346	0,00000	0,00000	0,00000	0,00000	0,00000	0,82861	-2,40242	0,01375		
	756	61 - 100	6,819	78,930	0,08561	0,00233	0,00000	0,00000	0,00000	0,00000	0,00000	0,43568	-2,36849	0,01685		
	612	100 - 200	13,471	139,475	0,09520	0,00217	0,00000	0,00000	0,00000	0,00000	0,00000	0,31287	-2,25171	0,01897		
	404	>200	62,577	484,252	0,12128	0,00158	0,00000	0,00000	0,00000	0,00000	0,00000	0,15609	-1,98035	0,02323		
PAL175	1701	00 - 30	0,650	12,987	0,04982	0,01077	0,00000	0,00000	0,00000	0,00000	0,00000	2,88149	-2,94828	0,01242		
	956	31 - 60	2,379	44,262	0,05357	0,00230	0,00000	0,00000	0,00000	0,00000	0,00000	1,32855	-2,87180	0,02063		
	756	61 - 100	4,690	78,930	0,05889	0,00181	0,00000	0,00000	0,00000	0,00000	0,00000	0,79652	-2,77135	0,02380		
	612	100 - 200	9,257	139,475	0,06530	0,00167	0,00000	0,00000	0,00000	0,00000	0,00000	0,47114	-2,66119	0,02677		
	404	>200	46,495	484,252	0,09036	0,00148	0,00000	0,00000	0,00000	0,00000	0,00000	0,26556	-2,30921	0,03011		
PAL180	1701	00 - 30	0,452	12,987	0,03506	0,00817	0,00000	0,00000	0,00000	0,00000	0,00000	2,91235	-3,31508	0,01738		
	956	31 - 60	1,697	44,262	0,03855	0,00176	0,00000	0,00000	0,00000	0,00000	0,00000	1,76852	-3,21637	0,02822		
	756	61 - 100	3,003	78,930	0,03763	0,00119	0,00000	0,00000	0,00000	0,00000	0,00000	1,13438	-3,24149	0,03643		
	612	100 - 200	6,507	139,475	0,04561	0,00123	0,00000	0,00000	0,00000	0,00000	0,00000	0,76527	-3,04090	0,03754		
	404	>200	32,047	484,252	0,06282	0,00110	0,00000	0,00000	0,00000	0,00000	0,00000	0,38430	-2,70267	0,04205		
PAL185	1701	00 - 30	0,266	12,987	0,02080	0,00536	0,00000	0,00000	0,00000	0,00000	0,00000	2,62474	-3,85197	0,02887		
	956	31 - 60	0,957	44,262	0,02141	0,00094	0,00000	0,00000	0,00000	0,00000	0,00000	2,30197	-3,82203	0,04991		
	756	61 - 100	1,908	78,930	0,02377	0,00067	0,00000	0,00000	0,00000	0,00000	0,00000	1,66760	-3,71530	0,05685		
	612	100 - 200	4,330	139,475	0,03048	0,00096	0,00000	0,00000	0,00000	0,00000	0,00000	1,07902	-3,45985	0,05530		
	404	>200	20,213	484,252	0,03974	0,00072	0,00000	0,00000	0,00000	0,00000	0,00000	0,52251	-3,18492	0,06487		
PAL190	1701	00 - 30	0,200	12,987	0,01558	0,00332	0,00000	0,00000	0,00000	0,00000	0,00000	2,32303	-4,14603	0,03833		
	956	31 - 60	0,599	44,262	0,01356	0,00057	0,00000	0,00000	0,00000	0,00000	0,00000	2,53253	-4,28713	0,07821		
	756	61 - 100	1,248	78,930	0,01561	0,00057	0,00000	0,00000	0,00000	0,00000	0,00000	2,12396	-4,14413	0,08586		
	612	100 - 200	2,832	139,475	0,01988	0,00073	0,00000	0,00000	0,00000	0,00000	0,00000	1,58417	-3,89811	0,08387		
	404	>200	12,265	484,252	0,02377	0,00047	0,00000	0,00000	0,00000	0,00000	0,00000	0,78444	-3,71508	0,10665		

Table 10.7 Variance components lobster for all assessment areas other than Shetland, including in the variance component analysis the year (Y), gender (G) and assessment area (A). Weighted GLMER results.

Weighted Glmer(AGY) Results for Other Areas Lobster													
Model Input			Actuals				Variance Components			Residuals	Fixed Effects		
Length	RC	N_Bin	Mean NAL	Mean N_Sex_Int	Actual Mean PAL	Actual Variance	VarComp Y	VarComp A	VarComp G	Error	Intercept	Var(Int)	
PAL095	1033	5-	1,132	2,619	0,38729	0,13867	0,03094	0,21533	0,00116	5,18048	-0,20928	0,04352	
	847	5 - 15	4,112	9,594	0,42939	0,05574	0,01844	0,23841	0,00095	1,10714	-0,46857	0,03321	
	300	15 - 25	8,047	19,763	0,40977	0,04353	0,07238	0,36526	0,00076	0,59830	-0,71579	0,04988	
	163	25 - 40	11,767	31,558	0,37226	0,04125	0,01795	0,67663	0,00370	0,45611	-1,03715	0,07845	
	203	40+	21,754	72,768	0,30366	0,03223	0,09391	0,38836	0,00695	0,54976	-0,98843	0,05925	
PAL100	1033	5-	0,529	2,619	0,18514	0,07479	0,00000	0,00028	0,01912	4,95776	-1,37212	0,01196	
	847	5 - 15	2,015	9,594	0,21037	0,02087	0,00000	0,00590	0,01090	1,21365	-1,33733	0,00747	
	300	15 - 25	4,167	19,763	0,21065	0,01165	0,00352	0,00939	0,00372	0,53558	-1,36366	0,00518	
	163	25 - 40	6,804	31,558	0,21713	0,00857	0,00616	0,08438	0,01301	0,30459	-1,42227	0,02005	
	203	40+	13,754	72,768	0,19159	0,00533	0,01476	0,00000	0,01536	0,20634	-1,46306	0,00973	
PAL105	1033	5-	0,305	2,619	0,10610	0,04636	0,00191	0,07341	0,00000	4,38699	-2,13133	0,02046	
	847	5 - 15	1,220	9,594	0,12749	0,01443	0,00000	0,03758	0,00112	1,91181	-1,90066	0,00812	
	300	15 - 25	2,653	19,763	0,13409	0,00889	0,01187	0,05997	0,00000	0,92679	-1,73221	0,01164	
	163	25 - 40	4,460	31,558	0,14164	0,00636	0,01247	0,04840	0,00000	0,55907	-1,71185	0,01044	
	203	40+	10,305	72,768	0,14039	0,00376	0,05190	0,03709	0,00000	0,27912	-1,93056	0,01160	
PAL110	1033	5-	0,215	2,619	0,07833	0,03672	0,00000	0,12801	0,00000	4,04114	-2,49273	0,03300	
	847	5 - 15	0,774	9,594	0,07926	0,00990	0,00461	0,08920	0,00209	2,44032	-2,47084	0,01772	
	300	15 - 25	1,667	19,763	0,08307	0,00691	0,02397	0,21034	0,00335	1,52642	-2,33610	0,03445	
	163	25 - 40	2,902	31,558	0,09135	0,00468	0,00000	0,15845	0,00000	0,98158	-2,37299	0,02438	
	203	40+	8,424	72,768	0,11346	0,00342	0,04144	0,18623	0,00000	0,35572	-2,12958	0,02883	
PAL115	1033	5-	0,132	2,619	0,04230	0,01799	0,17827	0,18804	0,05621	2,76605	-3,24793	0,09969	
	847	5 - 15	0,499	9,594	0,05169	0,00634	0,02731	0,21367	0,00000	2,63320	-2,77143	0,03627	
	300	15 - 25	1,100	19,763	0,05518	0,00418	0,05684	0,30654	0,00340	1,79892	-2,90886	0,05324	
	163	25 - 40	1,933	31,558	0,06033	0,00351	0,01323	0,42753	0,02160	1,33771	-2,36171	0,06488	
	203	40+	6,118	72,768	0,08425	0,00287	0,05998	0,18140	0,00002	0,58460	-2,52561	0,03177	
PAL120	1033	5-	0,114	2,619	0,03888	0,01776	0,12583	0,27132	0,00776	2,82540	-3,31095	0,08718	
	847	5 - 15	0,341	9,594	0,03652	0,00462	0,04926	0,23902	0,00020	2,60407	-3,29872	0,04606	
	300	15 - 25	0,760	19,763	0,03827	0,00292	0,13999	0,56456	0,03796	2,07845	-3,20675	0,11065	
	163	25 - 40	1,423	31,558	0,04517	0,00296	0,00000	0,64896	0,00864	1,62628	-2,82553	0,08351	
	203	40+	4,601	72,768	0,06233	0,00256	0,00094	0,11647	0,00964	0,86603	-2,75495	0,02261	
PAL125	1033	5-	0,066	2,619	0,02001	0,00765	0,05071	0,38709	0,06858	2,04229	-3,91473	0,14501	
	847	5 - 15	0,235	9,594	0,02486	0,00301	0,01615	0,64085	0,02571	2,40271	-3,76744	0,11247	
	300	15 - 25	0,547	19,763	0,02784	0,00194	0,02892	0,36673	0,04980	2,34984	-3,44997	0,08467	
	163	25 - 40	0,902	31,558	0,02819	0,00133	0,00000	0,41818	0,07557	2,02280	-3,41857	0,10159	
	203	40+	3,074	72,768	0,04194	0,00181	0,12347	0,12252	0,03300	1,18136	-3,16964	0,04932	
PAL130	1033	5-	0,064	2,619	0,02372	0,01240	0,13034	0,39116	0,00000	2,35902	-3,97303	0,12220	
	847	5 - 15	0,158	9,594	0,01641	0,00211	0,00000	0,21922	0,18026	2,20707	-4,19753	0,13867	
	300	15 - 25	0,317	19,763	0,01558	0,00093	0,13171	0,34032	0,02100	2,33681	-3,98137	0,08701	
	163	25 - 40	0,540	31,558	0,01730	0,00098	0,00000	1,77606	0,04291	1,97663	-3,91102	0,24352	
	203	40+	1,857	72,768	0,02505	0,00088	0,01608	0,19535	0,06172	1,72188	-3,53284	0,06309	

Table 10.8 Variance components lobster for all assessment areas other than Shetland, including in the variance component analysis the year (Y), gender (G) and assessment area (MA). Unweighted GLMER results.

Unweighted Glmer (AGY) Results for Other Areas Lobster												
Model Input			Actuals				Variance Components			Residuals	Fixed Effects	
Length	RC	N_Bin	Mean NAL	Mean N_Sex_Int	Actual Mean PAL	Actual PAL Variance	VarComp Y	VarComp MA	VarComp G	Error	Intercept	Var(Int)
PAL095	1033	5-	1,132	2,619	0,38729	0,13867	0,03532	0,29887	0,00000	5,21767	-0,38802	0,06426
	847	5 - 15	4,112	9,594	0,42939	0,05574	0,00594	0,39474	0,00000	1,13053	-0,36935	0,06743
	300	15 - 25	8,047	19,763	0,40977	0,04353	0,00000	0,40458	0,00000	0,67580	-0,47717	0,08203
	163	25 - 40	11,767	31,558	0,37226	0,04125	0,00000	0,69559	0,00000	0,54023	-0,69257	0,13969
	203	40+	21,754	72,768	0,30366	0,03223	0,00829	0,39835	0,00000	0,63685	-0,76828	0,09280
PAL100	1033	5-	0,529	2,619	0,18514	0,07479	0,00000	0,00000	0,00000	4,97534	-1,48190	0,00642
	847	5 - 15	2,015	9,594	0,21037	0,02087	0,00000	0,00000	0,00000	1,23811	-1,32267	0,00711
	300	15 - 25	4,167	19,763	0,21065	0,01165	0,00000	0,00000	0,00000	0,55483	-1,32102	0,02005
	163	25 - 40	6,804	31,558	0,21713	0,00857	0,00000	0,00000	0,00000	0,35692	-1,28247	0,03609
	203	40+	13,754	72,768	0,19159	0,00533	0,00000	0,00000	0,00000	0,23034	-1,43972	0,03181
PAL105	1033	5-	0,305	2,619	0,10610	0,04636	0,00000	0,00000	0,00000	4,45424	-2,13122	0,01020
	847	5 - 15	1,220	9,594	0,12749	0,01443	0,00000	0,00000	0,00000	1,96361	-1,92329	0,01061
	300	15 - 25	2,653	19,763	0,13409	0,00889	0,00000	0,00000	0,00000	1,00134	-1,86523	0,02871
	163	25 - 40	4,460	31,558	0,14164	0,00636	0,00000	0,00000	0,00000	0,64078	-1,80174	0,05046
	203	40+	10,305	72,768	0,14039	0,00376	0,00000	0,00000	0,00000	0,34300	-1,81207	0,04082
PAL110	1033	5-	0,215	2,619	0,07833	0,03672	0,00000	0,13703	0,00000	4,04186	-2,63020	0,04979
	847	5 - 15	0,774	9,594	0,07926	0,00990	0,00000	0,00000	0,00000	2,58676	-2,45244	0,01618
	300	15 - 25	1,667	19,763	0,08307	0,00691	0,00000	0,00000	0,00000	1,75215	-2,40139	0,04376
	163	25 - 40	2,902	31,558	0,09135	0,00468	0,00000	0,00000	0,00000	1,18523	-2,29727	0,07390
	203	40+	8,424	72,768	0,11346	0,00342	0,00000	0,00000	0,00000	0,50514	-2,05585	0,04897
PAL115	1033	5-	0,132	2,619	0,04230	0,01799	0,00000	0,00000	0,00000	2,85629	-3,11965	0,02389
	847	5 - 15	0,499	9,594	0,05169	0,00634	0,00000	0,00000	0,00000	2,81176	-2,90950	0,02409
	300	15 - 25	1,100	19,763	0,05518	0,00418	0,00000	0,00000	0,00000	2,13558	-2,84046	0,06394
	163	25 - 40	1,933	31,558	0,06033	0,00351	0,00000	0,00000	0,00000	1,69575	-2,74575	0,10822
	203	40+	6,118	72,768	0,08425	0,00287	0,00000	0,00000	0,00000	0,75768	-2,38593	0,06384
PAL120	1033	5-	0,114	2,619	0,03888	0,01776	0,00000	0,00000	0,00000	2,88376	-3,20753	0,02590
	847	5 - 15	0,341	9,594	0,03652	0,00462	0,00000	0,00000	0,00000	2,76486	-3,27272	0,03355
	300	15 - 25	0,760	19,763	0,03827	0,00292	0,00000	0,00000	0,00000	2,55873	-3,22402	0,09056
	163	25 - 40	1,423	31,558	0,04517	0,00296	0,00000	0,00000	0,00000	2,09750	-3,05111	0,14225
	203	40+	4,601	72,768	0,06233	0,00256	0,00000	0,00000	0,00000	1,03326	-2,71096	0,08428
PAL125	1033	5-	0,066	2,619	0,02001	0,00765	0,00000	0,00000	0,00000	2,03161	-3,89149	0,04937
	847	5 - 15	0,235	9,594	0,02486	0,00301	0,00000	0,00000	0,00000	2,59546	-3,66947	0,04871
	300	15 - 25	0,547	19,763	0,02784	0,00194	0,00000	0,00000	0,00000	2,65022	-3,55296	0,12315
	163	25 - 40	0,902	31,558	0,02819	0,00133	0,00000	0,00000	0,00000	2,37477	-3,54025	0,22389
	203	40+	3,074	72,768	0,04194	0,00181	0,00000	0,00000	0,00000	1,39169	-3,12869	0,12258
PAL130	1033	5-	0,064	2,619	0,02372	0,01240	0,00000	0,00000	0,00000	2,34339	-3,71755	0,04181
	847	5 - 15	0,158	9,594	0,01641	0,00211	0,00000	0,00000	0,00000	2,27485	-4,09325	0,07314
	300	15 - 25	0,317	19,763	0,01558	0,00093	0,00000	0,00000	0,00000	2,61890	-4,14614	0,21725
	163	25 - 40	0,540	31,558	0,01730	0,00098	0,00000	0,00000	0,00000	2,60062	-4,03947	0,36070
	203	40+	1,857	72,768	0,02505	0,00088	0,00000	0,00000	0,00000	1,92527	-3,66150	0,20165

Table 10.9 Variance components for crab for all assessment areas other than Shetland, including in the variance component analysis the year (Y), gender (G) and assessment area (MA). Weighted GLMER results.

Weighted Glmer(AGY) Results for Other Areas Crab													
Model Input			Actuals				Variance components			Residuals	Fixed Effects		
Length Bin	RC	N_Bin	Mean NAL	Mean N_Bin	Actual Mean PAL	Actual PAL Variance	VarComp Y	VarComp MA	VarComp G	Error	Intercept	Var Intercept	
PAL145	1701	00 - 30	2,464	12,987	0,18858	0,04714	0,02258	0,46421	0,06708	2,77404	-2,01568	0,09232	
	956	31 - 60	7,785	44,262	0,17611	0,01565	0,01246	0,50591	0,07465	0,92168	-2,22597	0,09364	
	756	61 - 100	12,927	78,930	0,16499	0,01185	0,01569	0,80438	0,12760	0,70842	-2,38720	0,14901	
	612	100 - 200	19,332	139,475	0,14153	0,01035	0,03605	1,13746	0,16234	0,62010	-2,71411	0,20191	
	404	>200	27,542	484,252	0,07461	0,00611	0,09500	0,49123	0,26347	0,69699	-2,66250	0,19683	
PAL150	1701	00 - 30	2,469	12,987	0,19067	0,03521	0,01031	0,13492	0,02359	2,29208	-1,74658	0,03082	
	956	31 - 60	8,164	44,262	0,18509	0,00849	0,00775	0,16767	0,03204	0,39802	-1,94865	0,03619	
	756	61 - 100	13,908	78,930	0,17747	0,00619	0,00429	0,16614	0,03934	0,29735	-1,95293	0,03811	
	612	100 - 200	22,114	139,475	0,16030	0,00536	0,01195	0,18566	0,05076	0,22580	-2,02003	0,04608	
	404	>200	52,455	484,252	0,12077	0,00425	0,02780	0,08465	0,07947	0,25382	-1,96772	0,05254	
PAL155	1701	00 - 30	2,110	12,987	0,15992	0,02652	0,00146	0,01364	0,00942	2,20664	-1,74589	0,00770	
	956	31 - 60	7,190	44,262	0,16231	0,00447	0,00630	0,02291	0,00433	0,27455	-1,79268	0,00636	
	756	61 - 100	12,840	78,930	0,16297	0,00282	0,00018	0,01956	0,00905	0,15274	-1,77257	0,00729	
	612	100 - 200	21,592	139,475	0,15575	0,00242	0,00297	0,03383	0,01117	0,11958	-1,78972	0,00988	
	404	>200	68,062	484,252	0,14295	0,00189	0,00837	0,00699	0,00997	0,10832	-1,74286	0,00689	
PAL160	1701	00 - 30	1,867	12,987	0,14034	0,02508	0,00604	0,01114	0,00000	2,43074	-1,80046	0,00309	
	956	31 - 60	6,223	44,262	0,14025	0,00405	0,00103	0,02785	0,00000	0,32410	-1,75369	0,00416	
	756	61 - 100	11,443	78,930	0,14514	0,00280	0,00356	0,00364	0,00000	0,17153	-1,82704	0,00121	
	612	100 - 200	20,466	139,475	0,14691	0,00189	0,00483	0,00678	0,00000	0,11517	-1,77663	0,00160	
	404	>200	77,181	484,252	0,15520	0,00122	0,00803	0,00727	0,00048	0,06062	-1,68779	0,00214	
PAL165	1701	00 - 30	1,327	12,987	0,10153	0,02113	0,02779	0,05516	0,00781	2,72984	-2,11469	0,01554	
	956	31 - 60	4,877	44,262	0,11040	0,00370	0,00396	0,06366	0,00909	0,44604	-1,94602	0,01321	
	756	61 - 100	8,743	78,930	0,11035	0,00257	0,00169	0,04353	0,01746	0,25195	-1,99458	0,01432	
	612	100 - 200	16,382	139,475	0,11658	0,00195	0,00132	0,02870	0,01695	0,15734	-1,97502	0,01216	
	404	>200	71,993	484,252	0,14112	0,00137	0,00144	0,02829	0,01872	0,06329	-1,87601	0,01316	
PAL170	1701	00 - 30	0,961	12,987	0,07149	0,01332	0,01300	0,09837	0,03592	2,66877	-2,32555	0,03390	
	956	31 - 60	3,697	44,262	0,08299	0,00346	0,01365	0,07468	0,03504	0,75216	-2,19266	0,02873	
	756	61 - 100	6,819	78,930	0,08561	0,00233	0,00098	0,07069	0,04679	0,36951	-2,15450	0,03182	
	612	100 - 200	13,471	139,475	0,09520	0,00217	0,01073	0,07457	0,05430	0,21321	-2,11949	0,03652	
	404	>200	62,577	484,252	0,12128	0,00158	0,00371	0,01966	0,03937	0,09350	-2,05839	0,02275	
PAL175	1701	00 - 30	0,650	12,987	0,04982	0,01077	0,02480	0,19468	0,11916	2,75541	-2,62293	0,08925	
	956	31 - 60	2,379	44,262	0,05357	0,00230	0,00022	0,13672	0,06220	1,17145	-2,56545	0,04813	
	756	61 - 100	4,690	78,930	0,05889	0,00181	0,01162	0,13585	0,08368	0,62249	-2,43345	0,05818	
	612	100 - 200	9,257	139,475	0,06530	0,00167	0,01849	0,09559	0,07355	0,33041	-2,48580	0,04929	
	404	>200	46,495	484,252	0,09036	0,00148	0,01349	0,09693	0,05954	0,17503	-2,47604	0,04299	
PAL180	1701	00 - 30	0,452	12,987	0,03506	0,00817	0,00000	0,26737	0,10159	2,80698	-3,17279	0,08955	
	956	31 - 60	1,697	44,262	0,03855	0,00176	0,01211	0,20912	0,08758	1,53412	-2,90446	0,07095	
	756	61 - 100	3,003	78,930	0,03763	0,00119	0,00768	0,13945	0,09475	0,93341	-2,88975	0,06439	
	612	100 - 200	6,507	139,475	0,04561	0,00123	0,02452	0,17316	0,10577	0,52608	-2,86372	0,07435	
	404	>200	32,047	484,252	0,06282	0,00110	0,03025	0,07448	0,05379	0,28142	-2,83636	0,03943	
PAL185	1701	00 - 30	0,266	12,987	0,02080	0,00536	0,00000	0,28972	0,19866	2,51669	-3,47596	0,14206	
	956	31 - 60	0,957	44,262	0,02141	0,00094	0,05217	0,21563	0,10133	1,99241	-3,42197	0,08459	
	756	61 - 100	1,908	78,930	0,02377	0,00067	0,00937	0,17684	0,10621	1,41641	-3,30322	0,07497	
	612	100 - 200	4,330	139,475	0,03048	0,00096	0,03311	0,21071	0,08607	0,79228	-3,23694	0,06968	
	404	>200	20,213	484,252	0,03974	0,00072	0,04625	0,16545	0,05264	0,39950	-3,39020	0,05171	
PAL190	1701	00 - 30	0,200	12,987	0,01558	0,00332	0,04630	0,64048	0,16596	2,18016	-3,54000	0,17062	
	956	31 - 60	0,599	44,262	0,01356	0,00057	0,04299	0,28745	0,16885	2,24368	-3,81709	0,12714	
	756	61 - 100	1,248	78,930	0,01561	0,00057	0,03769	0,26366	0,07531	1,84052	-3,70694	0,07259	
	612	100 - 200	2,832	139,475	0,01988	0,00073	0,06898	0,24489	0,05162	1,22383	-3,66851	0,06041	
	404	>200	12,265	484,252	0,02377	0,00047	0,11219	0,25392	0,03127	0,62719	-3,92577	0,05894	

Table 10.10 Variance components crab for all assessment areas other than Shetland, including in the variance component analysis the year and assessment area. Unweighted GLMER results.

Unweighted Glmer(AGY) Results for Other Areas Crab													
Model Input			Actuals				Variance components			Residuals	Fixed Effects		
Length Bin	RC	N_Bin	Mean NAL	Mean N_Bin	Actual Mean PAL	Actual PAL Variance	VarComp Y	VarComp MA	VarComp G	Error	Intercept	Var Intercept	
PAL145	1701	00 - 30	2,464	12,987	0,18858	0,04714	0,00000	0,15329	0,00000	2,94681	-1,68732	0,03509	
	956	31 - 60	7,785	44,262	0,17611	0,01565	0,00000	0,00000	0,00000	1,23100	-1,54295	0,00721	
	756	61 - 100	12,927	78,930	0,16499	0,01185	0,00000	0,00000	0,00000	1,02240	-1,62153	0,00958	
	612	100 - 200	19,332	139,475	0,14153	0,01035	0,00000	0,00000	0,00000	1,12106	-1,80264	0,01345	
	404	>200	27,542	484,252	0,07461	0,00611	0,00000	0,00000	0,00000	1,23960	-2,51795	0,03585	
PAL150	1701	00 - 30	2,469	12,987	0,19067	0,03521	0,00000	0,00000	0,00000	2,41882	-1,44569	0,00381	
	956	31 - 60	8,164	44,262	0,18509	0,00849	0,00000	0,00000	0,00000	0,52699	-1,48226	0,00693	
	756	61 - 100	13,908	78,930	0,17747	0,00619	0,00000	0,00000	0,00000	0,41619	-1,53359	0,00904	
	612	100 - 200	22,114	139,475	0,16030	0,00536	0,00000	0,00000	0,00000	0,41531	-1,65600	0,01214	
	404	>200	52,455	484,252	0,12077	0,00425	0,00000	0,00000	0,00000	0,41399	-1,98518	0,02331	
PAL155	1701	00 - 30	2,110	12,987	0,15992	0,02652	0,00000	0,00000	0,00000	2,26206	-1,65880	0,00438	
	956	31 - 60	7,190	44,262	0,16231	0,00447	0,00000	0,00000	0,00000	0,31200	-1,64117	0,00769	
	756	61 - 100	12,840	78,930	0,16297	0,00282	0,00000	0,00000	0,00000	0,17248	-1,63631	0,00967	
	612	100 - 200	21,592	139,475	0,15575	0,00242	0,00000	0,00000	0,00000	0,16175	-1,69019	0,01243	
	404	>200	68,062	484,252	0,14295	0,00189	0,00000	0,00000	0,00000	0,13147	-1,79096	0,02020	
PAL160	1701	00 - 30	1,867	12,987	0,14034	0,02508	0,00000	0,00000	0,00000	2,44482	-1,81251	0,00487	
	956	31 - 60	6,223	44,262	0,14025	0,00405	0,00000	0,00000	0,00000	0,33361	-1,81318	0,00867	
	756	61 - 100	11,443	78,930	0,14514	0,00280	0,00000	0,00000	0,00000	0,18038	-1,77322	0,01063	
	612	100 - 200	20,466	139,475	0,14691	0,00189	0,00000	0,00000	0,00000	0,12478	-1,75908	0,01304	
	404	>200	77,181	484,252	0,15520	0,00122	0,00000	0,00000	0,00000	0,06791	-1,69442	0,01888	
PAL165	1701	00 - 30	1,327	12,987	0,10153	0,02113	0,00000	0,00000	0,00000	0,00618	2,80937	-2,18566	0,00962
	956	31 - 60	4,877	44,262	0,11040	0,00370	0,00000	0,00000	0,00000	0,48624	-2,08671	0,01065	
	756	61 - 100	8,743	78,930	0,11035	0,00257	0,00000	0,00000	0,00000	0,28670	-2,08722	0,01344	
	612	100 - 200	16,382	139,475	0,11658	0,00195	0,00000	0,00000	0,00000	0,18655	-2,02522	0,01587	
	404	>200	71,993	484,252	0,14112	0,00137	0,00000	0,00000	0,00000	0,09888	-1,80604	0,02042	
PAL170	1701	00 - 30	0,961	12,987	0,07149	0,01332	0,00000	0,00000	0,00000	2,70022	-2,56406	0,00885	
	956	31 - 60	3,697	44,262	0,08299	0,00346	0,00000	0,00000	0,00000	0,82861	-2,40242	0,01375	
	756	61 - 100	6,819	78,930	0,08561	0,00233	0,00000	0,00000	0,00000	0,43568	-2,36849	0,01685	
	612	100 - 200	13,471	139,475	0,09520	0,00217	0,00000	0,00000	0,00000	0,31287	-2,25171	0,01897	
	404	>200	62,577	484,252	0,12128	0,00158	0,00000	0,00000	0,00000	0,15609	-1,98035	0,02323	
PAL175	1701	00 - 30	0,650	12,987	0,04982	0,01077	0,00000	0,00000	0,00000	2,88149	-2,94828	0,01242	
	956	31 - 60	2,379	44,262	0,05357	0,00230	0,00000	0,00000	0,00000	1,32855	-2,87180	0,02063	
	756	61 - 100	4,690	78,930	0,05889	0,00181	0,00000	0,00000	0,00000	0,79652	-2,77135	0,02380	
	612	100 - 200	9,257	139,475	0,06530	0,00167	0,00000	0,00000	0,00000	0,47114	-2,66119	0,02677	
	404	>200	46,495	484,252	0,09036	0,00148	0,00000	0,00000	0,00000	0,26556	-2,30921	0,03011	
PAL180	1701	00 - 30	0,452	12,987	0,03506	0,00817	0,00000	0,00000	0,00000	2,91235	-3,31508	0,01738	
	956	31 - 60	1,697	44,262	0,03855	0,00176	0,00000	0,00000	0,00000	1,76852	-3,21637	0,02822	
	756	61 - 100	3,003	78,930	0,03763	0,00119	0,00000	0,00000	0,00000	1,13438	-3,24149	0,03643	
	612	100 - 200	6,507	139,475	0,04561	0,00123	0,00000	0,00000	0,00000	0,76527	-3,04090	0,03754	
	404	>200	32,047	484,252	0,06282	0,00110	0,00000	0,00000	0,00000	0,38430	-2,70267	0,04205	
PAL185	1701	00 - 30	0,266	12,987	0,02080	0,00536	0,00000	0,00000	0,00000	2,62474	-3,85197	0,02887	
	956	31 - 60	0,957	44,262	0,02141	0,00094	0,00000	0,00000	0,00000	2,30197	-3,82203	0,04991	
	756	61 - 100	1,908	78,930	0,02377	0,00067	0,00000	0,00000	0,00000	1,66760	-3,71530	0,05685	
	612	100 - 200	4,330	139,475	0,03048	0,00096	0,00000	0,00000	0,00000	1,07902	-3,45985	0,05530	
	404	>200	20,213	484,252	0,03974	0,00072	0,00000	0,00000	0,00000	0,52251	-3,18492	0,06487	
PAL190	1701	00 - 30	0,200	12,987	0,01558	0,00332	0,00000	0,00000	0,00000	2,32303	-4,14603	0,03833	
	956	31 - 60	0,599	44,262	0,01356	0,00057	0,00000	0,00000	0,00000	2,53253	-4,28713	0,07821	
	756	61 - 100	1,248	78,930	0,01561	0,00057	0,00000	0,00000	0,00000	2,12396	-4,14413	0,08586	
	612	100 - 200	2,832	139,475	0,01988	0,00073	0,00000	0,00000	0,00000	1,58417	-3,89811	0,08387	
	404	>200	12,265	484,252	0,02377	0,00047	0,00000	0,00000	0,00000	0,78444	-3,71508	0,10665	

Table 10.11 Variance components for scallops for all assessment areas other than the Irish Sea, including in the variance component analysis the statistical area (S), month (M), year (Y) and management area (A). Weighted GLMER results.

Weighted GLMM (GlmerAYMS) Results for Other Areas Scallops														
Model Input			Actuals				Variance components				Residuals		Fixed Effects	
Length Bin	RC	N_Bin	Mean NAL	Mean N_Bin	Actual Mean PAL	Actual PAL Variance	VarComp S	VarComp M	VarComp Y	VarComp A	Error	Intercept	Var Intercept	
PAL100	511	000 - 100	5,192	93,485	0,05412	0,00323	0,47290	0,01477	0,09360	1,00420	1,06767	-4,52394	0,28328	
	300	100 - 125	7,157	108,507	0,06574	0,00394	1,04867	0,03976	0,08082	0,00000	0,86107	-3,35185	0,06332	
	311	125 - 175	15,132	152,116	0,09775	0,00756	0,57898	0,03436	0,04426	0,33998	0,85260	-2,84774	0,07667	
	216	175 - 225	21,231	200,569	0,10556	0,00739	0,51487	0,08834	0,08438	0,11321	0,56335	-2,63735	0,05116	
	215	>225	37,944	264,126	0,14025	0,00985	0,36078	0,02001	0,05134	0,09267	0,57880	-2,05679	0,03573	
PAL105	511	000 - 100	10,397	93,485	0,10856	0,00622	1,55945	0,01540	0,05206	1,00992	0,55017	-3,97418	0,33740	
	300	100 - 125	12,943	108,507	0,11960	0,00527	0,83492	0,01370	0,02748	0,00000	0,44198	-2,83350	0,04388	
	311	125 - 175	19,765	152,116	0,12836	0,00558	0,21138	0,00993	0,01366	0,19184	0,46712	-2,26871	0,03762	
	216	175 - 225	28,421	200,569	0,14141	0,00772	0,32902	0,04057	0,02974	0,02816	0,37517	-2,06526	0,02152	
	215	>225	44,586	264,126	0,16634	0,00593	0,25512	0,00712	0,01636	0,03551	0,28951	-1,71193	0,01694	
PAL110	511	000 - 100	13,706	93,485	0,14310	0,00657	1,49484	0,00255	0,00844	0,91132	0,36332	-3,29135	0,29365	
	300	100 - 125	18,350	108,507	0,16956	0,00669	0,60170	0,01005	0,01784	0,00000	0,31071	-2,20752	0,03056	
	311	125 - 175	27,052	152,116	0,17632	0,00619	0,08612	0,00724	0,00925	0,09699	0,29505	-1,70571	0,01888	
	216	175 - 225	37,000	200,569	0,18372	0,00778	0,29220	0,02780	0,02996	0,02140	0,24113	-1,61393	0,01799	
	215	>225	55,516	264,126	0,20910	0,00562	0,17730	0,00559	0,00728	0,21597	0,14773	-1,52393	0,04563	
PAL115	511	000 - 100	14,894	93,485	0,15544	0,00575	1,47666	0,00726	0,00562	0,39393	0,29988	-2,84308	0,17798	
	300	100 - 125	17,513	108,507	0,16230	0,00503	0,27475	0,00576	0,00450	0,19572	0,22081	-2,20802	0,04788	
	311	125 - 175	23,503	152,116	0,15450	0,00506	0,13069	0,01227	0,00518	0,02346	0,19340	-1,73000	0,00943	
	216	175 - 225	30,204	200,569	0,15010	0,00362	0,10679	0,00808	0,01886	0,00000	0,19970	-1,71944	0,00606	
	215	>225	39,121	264,126	0,14848	0,00276	0,10997	0,00456	0,01243	0,02887	0,11419	-1,77791	0,01084	
PAL120	511	000 - 100	14,935	93,485	0,15797	0,00508	0,34608	0,00535	0,00379	0,00000	0,28750	-1,84149	0,02173	
	300	100 - 125	17,893	108,507	0,16496	0,00457	0,20008	0,01355	0,00613	0,00000	0,21005	-1,72499	0,01151	
	311	125 - 175	24,803	152,116	0,16331	0,00400	0,08660	0,00850	0,00909	0,00000	0,18017	-1,57953	0,00450	
	216	175 - 225	31,491	200,569	0,15722	0,00504	0,04980	0,03093	0,02849	0,00000	0,23651	-1,62201	0,00729	
	215	>225	36,256	264,126	0,13918	0,00376	0,08979	0,01000	0,00627	0,01892	0,18898	-1,86292	0,00824	
PAL125	511	000 - 100	12,157	93,485	0,13074	0,00468	0,22094	0,00044	0,01151	0,00000	0,36825	-1,85480	0,01532	
	300	100 - 125	13,717	108,507	0,12599	0,00498	0,20712	0,00250	0,02874	0,00000	0,27988	-1,84427	0,01320	
	311	125 - 175	16,065	152,116	0,10711	0,00340	0,09817	0,00708	0,01378	0,04788	0,37762	-2,03578	0,01269	
	216	175 - 225	19,694	200,569	0,09821	0,00378	0,14698	0,02883	0,03236	0,01734	0,39503	-2,22388	0,01368	
	215	>225	19,935	264,126	0,07722	0,00237	0,21262	0,01304	0,01447	0,00000	0,37441	-2,57740	0,00925	
PAL130	511	000 - 100	9,603	93,485	0,10559	0,00580	0,20327	0,00388	0,01420	0,06222	0,62622	-1,70884	0,02877	
	300	100 - 125	9,950	108,507	0,09148	0,00449	0,22221	0,01727	0,02767	0,02933	0,53941	-1,95718	0,02086	
	311	125 - 175	12,526	152,116	0,08372	0,00410	0,25010	0,01872	0,01439	0,19590	0,63435	-2,36132	0,04033	
	216	175 - 225	15,583	200,569	0,07814	0,00439	0,46590	0,06944	0,03422	0,05130	0,50537	-2,53694	0,03271	
	215	>225	15,451	264,126	0,06011	0,00265	0,64254	0,02781	0,05743	0,00000	0,55894	-3,00429	0,02720	
PAL135	511	000 - 100	6,023	93,485	0,06781	0,00418	0,31519	0,01327	0,01102	0,12415	0,88179	-2,08646	0,04959	
	300	100 - 125	5,417	108,507	0,04979	0,00260	0,35806	0,05038	0,04550	0,10942	0,98820	-2,49351	0,04615	
	311	125 - 175	6,481	152,116	0,04342	0,00247	0,68119	0,14488	0,05582	0,20099	1,01578	-3,25877	0,07027	
	216	175 - 225	7,597	200,569	0,03808	0,00207	0,81652	0,09881	0,02738	0,06152	0,65754	-3,40458	0,04782	
	215	>225	6,986	264,126	0,02711	0,00103	0,95096	0,04172	0,04666	0,00000	0,85638	-3,86332	0,03735	
PAL140	511	000 - 100	3,474	93,485	0,04002	0,00323	0,55417	0,05901	0,02233	0,15903	1,46748	-2,40593	0,07680	
	300	100 - 125	2,990	108,507	0,02748	0,00150	0,76168	0,12978	0,04607	0,34430	1,36334	-3,01549	0,11197	
	311	125 - 175	4,077	152,116	0,02734	0,00145	0,55145	0,02833	0,08177	0,49779	1,22591	-3,71390	0,10380	
	216	175 - 225	4,981	200,569	0,02505	0,00121	1,39234	0,18361	0,07108	0,03932	0,93951	-3,97064	0,07399	
	215	>225	4,423	264,126	0,01706	0,00064	1,00548	0,02108	0,07798	0,17571	1,11647	-4,42641	0,07831	
PAL145	511	000 - 100	1,785	93,485	0,02078	0,00157	1,01127	0,09665	0,03386	0,13872	1,78487	-3,21680	0,10765	
	300	100 - 125	1,253	108,507	0,01152	0,00054	0,99856	0,19586	0,02762	0,16233	1,73748	-4,15671	0,10463	
	311	125 - 175	1,484	152,116	0,00995	0,00038	0,72682	0,01793	0,17949	0,34745	1,61127	-4,78153	0,10064	
	216	175 - 225	2,032	200,569	0,01025	0,00042	2,89000	0,47512	0,12998	0,00000	1,29064	-5,07245	0,14933	
	215	>225	1,949	264,126	0,00755	0,00028	2,29715	0,16130	0,02392	0,48578	1,27797	-5,63831	0,19364	

Table 10.12 Variance components for scallops for all assessment other than the Irish Sea, including in the variance component analysis, the year (Y) and assessment area (A). Weighted GLMER results.

Weighted GLMM Results (GlmerAY) for Other Areas Scallops												
Model Input			Actuals				Variance Components		Residuals	Fixed Effects		
Length Bin	RC	N_Bin	Mean NAL	Mean N_Bin	Actual Mean PAL	Actual Variance	VarComp Y	VarComp A	Error	Intercept	Var Intercept	
PAL100	511	000 - 100	5,192	93,485	0,05412	0,00323	0,08956	0,97244	1,10220	-4,37946	0,23690	
	300	100 - 125	7,157	108,507	0,06574	0,00394	0,08859	0,11967	1,00909	-3,01020	0,03055	
	311	125 - 175	15,132	152,116	0,09775	0,00756	0,04525	0,23793	0,96586	-2,46693	0,03950	
	216	175 - 225	21,231	200,569	0,10556	0,00739	0,04471	0,12655	0,80225	-2,42568	0,02421	
	215	>225	37,944	264,126	0,14025	0,00985	0,03160	0,29077	0,72644	-2,14377	0,05282	
PAL105	511	000 - 100	10,397	93,485	0,10856	0,00622	0,04361	0,99151	0,60129	-3,73382	0,22139	
	300	100 - 125	12,943	108,507	0,11960	0,00527	0,03148	0,11566	0,53877	-2,54679	0,02294	
	311	125 - 175	19,765	152,116	0,12836	0,00558	0,01543	0,19584	0,53958	-2,13370	0,03029	
	216	175 - 225	28,421	200,569	0,14141	0,00772	0,01696	0,09484	0,56905	-1,91885	0,01612	
	215	>225	44,586	264,126	0,16634	0,00593	0,00936	0,27406	0,38473	-1,91540	0,04761	
PAL110	511	000 - 100	13,706	93,485	0,14310	0,00657	0,00939	0,57933	0,40645	-3,06991	0,12444	
	300	100 - 125	18,350	108,507	0,16956	0,00669	0,01902	0,16217	0,37762	-2,02598	0,02737	
	311	125 - 175	27,052	152,116	0,17632	0,00619	0,00682	0,12890	0,32486	-1,69844	0,01962	
	216	175 - 225	37,000	200,569	0,18372	0,00778	0,03212	0,07696	0,37763	-1,59365	0,01494	
	215	>225	55,516	264,126	0,20910	0,00562	0,01513	0,38706	0,19923	-1,59010	0,06674	
PAL115	511	000 - 100	14,894	93,485	0,15544	0,00575	0,00517	0,44274	0,35603	-2,69168	0,09389	
	300	100 - 125	17,513	108,507	0,16230	0,00503	0,01004	0,22083	0,25895	-2,14853	0,03523	
	311	125 - 175	23,503	152,116	0,15450	0,00506	0,00696	0,07410	0,24312	-1,76839	0,01181	
	216	175 - 225	30,204	200,569	0,15010	0,00362	0,01669	0,00952	0,25708	-1,74433	0,00357	
	215	>225	39,121	264,126	0,14848	0,00276	0,01924	0,09242	0,15214	-1,79385	0,01791	
PAL120	511	000 - 100	14,935	93,485	0,15797	0,00508	0,00256	0,11555	0,32751	-1,79206	0,02532	
	300	100 - 125	17,893	108,507	0,16496	0,00457	0,00525	0,02292	0,25692	-1,76554	0,00530	
	311	125 - 175	24,803	152,116	0,16331	0,00400	0,00697	0,00159	0,21771	-1,64274	0,00121	
	216	175 - 225	31,491	200,569	0,15722	0,00504	0,02143	0,00625	0,27628	-1,66454	0,00349	
	215	>225	36,256	264,126	0,13918	0,00376	0,01038	0,00743	0,23245	-1,81281	0,00266	
PAL125	511	000 - 100	12,157	93,485	0,13074	0,00468	0,01058	0,11519	0,38987	-1,75679	0,02616	
	300	100 - 125	13,717	108,507	0,12599	0,00498	0,03036	0,13810	0,30920	-1,98418	0,02513	
	311	125 - 175	16,065	152,116	0,10711	0,00340	0,01255	0,05218	0,42271	-2,06781	0,00936	
	216	175 - 225	19,694	200,569	0,09821	0,00378	0,01851	0,04418	0,50306	-2,17402	0,00913	
	215	>225	19,935	264,126	0,07722	0,00237	0,00984	0,08605	0,47822	-2,35343	0,01604	
PAL130	511	000 - 100	9,603	93,485	0,10559	0,00580	0,01166	0,18230	0,65040	-1,72758	0,03965	
	300	100 - 125	9,950	108,507	0,09148	0,00449	0,02919	0,23730	0,58676	-2,02487	0,03928	
	311	125 - 175	12,526	152,116	0,08372	0,00410	0,01366	0,21665	0,72884	-2,32734	0,03324	
	216	175 - 225	15,583	200,569	0,07814	0,00439	0,01809	0,17193	0,80449	-2,45159	0,02792	
	215	>225	15,451	264,126	0,06011	0,00265	0,03333	0,15812	0,77305	-2,63109	0,03062	
PAL135	511	000 - 100	6,023	93,485	0,06781	0,00418	0,01556	0,22567	0,92624	-2,01171	0,04901	
	300	100 - 125	5,417	108,507	0,04979	0,00260	0,03612	0,20376	1,09061	-2,41671	0,03559	
	311	125 - 175	6,481	152,116	0,04342	0,00247	0,02262	0,34266	1,18513	-3,01125	0,05280	
	216	175 - 225	7,597	200,569	0,03808	0,00207	0,09002	0,31122	1,04657	-3,18139	0,05629	
	215	>225	6,986	264,126	0,02711	0,00103	0,06637	0,46825	1,13216	-3,43874	0,08656	
PAL140	511	000 - 100	3,474	93,485	0,04002	0,00323	0,02627	0,40934	1,56262	-2,26979	0,08710	
	300	100 - 125	2,990	108,507	0,02748	0,00150	0,04927	0,46765	1,61756	-2,90634	0,07618	
	311	125 - 175	4,077	152,116	0,02734	0,00145	0,07896	0,62644	1,41526	-3,55299	0,10008	
	216	175 - 225	4,981	200,569	0,02505	0,00121	0,12703	0,34474	1,43509	-3,59444	0,06604	
	215	>225	4,423	264,126	0,01706	0,00064	0,03281	0,69742	1,40085	-3,99179	0,12388	
PAL145	511	000 - 100	1,785	93,485	0,02078	0,00157	0,05859	0,53947	1,93574	-2,90820	0,11828	
	300	100 - 125	1,253	108,507	0,01152	0,00054	0,12152	0,73969	1,95361	-3,86604	0,13078	
	311	125 - 175	1,484	152,116	0,00995	0,00038	0,21662	0,70131	1,88075	-4,59686	0,12821	
	216	175 - 225	2,032	200,569	0,01025	0,00042	0,20245	0,35780	1,85215	-4,55643	0,08038	
	215	>225	1,949	264,126	0,00755	0,00028	0,19194	1,32514	1,69767	-5,00860	0,25100	

Table 10.13 MWCV estimates for lobster for all areas except Shetland, for the existing sampling regimes 2007 to 2016, for all different ways of calculating the error variance.

Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	Females	NR	1	1	1	1		2	3	1	3	1
		N	2,0	17,0	10,0	13,0		7,5	14,3	2,0	7,3	10,0
		MWCV_AGYIM_W	49,3%	76,8%	50,0%	62,1%		59,5%	59,7%	80,6%	38,3%	57,1%
		MWCV_AGY_W	50,1%	78,9%	50,2%	64,5%		59,8%	61,5%	80,4%	38,5%	59,2%
		MWCV_AGY_U	47,0%	83,4%	50,4%	66,2%		59,1%	61,4%	80,0%	39,2%	57,8%
	Males	NR	1	1	1	1		2	3	1	3	1
		N	2,0	24,0	24,0	15,0		12,5	11,0	0,0	9,0	16,0
		MWCV_AGYIM_W	74,9%	72,3%	42,0%	83,9%		58,7%	59,9%	31,5%	46,4%	51,5%
		MWCV_AGY_W	75,3%	75,2%	45,6%	86,5%		59,0%	61,9%	30,2%	47,4%	54,0%
		MWCV_AGY_U	76,2%	77,6%	46,0%	86,5%		59,9%	60,0%	26,4%	47,9%	51,4%
East Coast	Females	NR	7	7	9	12	11	16	17	19	11	14
		N	20,0	14,6	6,0	4,8	10,6	16,4	11,8	14,4	8,3	5,7
		MWCV_AGYIM_W	32,0%	27,7%	35,3%	29,9%	22,3%	19,7%	39,0%	16,2%	28,3%	28,8%
		MWCV_AGY_W	32,9%	28,0%	35,0%	30,6%	23,0%	22,8%	39,9%	17,4%	29,9%	29,9%
		MWCV_AGY_U	32,9%	28,4%	35,9%	30,8%	23,1%	22,6%	39,2%	17,8%	30,4%	31,1%
	Males	NR	7	7	12	12	13	16	17	20	11	14
		N	20,6	22,1	11,8	13,1	16,6	20,3	10,2	22,4	8,9	5,6
		MWCV_AGYIM_W	29,1%	26,4%	21,2%	35,1%	29,6%	24,7%	36,1%	19,1%	30,6%	35,6%
		MWCV_AGY_W	30,0%	27,9%	22,5%	35,6%	30,0%	28,2%	38,1%	21,9%	31,8%	36,7%
		MWCV_AGY_U	31,1%	28,1%	23,1%	35,5%	30,2%	28,4%	36,6%	21,9%	32,1%	36,2%
Hebrides	Females	NR	8	10	11	16	7	3	23	23	23	25
		N	45,1	50,0	21,4	43,6	20,4	45,0	14,3	33,8	30,6	32,9
		MWCV_AGYIM_W	20,1%	23,6%	25,1%	22,8%	31,7%	18,6%	23,6%	17,8%	16,6%	18,9%
		MWCV_AGY_W	22,5%	25,2%	26,0%	24,4%	35,8%	23,3%	23,0%	18,6%	17,9%	20,2%
		MWCV_AGY_U	22,7%	25,4%	26,6%	24,3%	35,3%	23,9%	23,4%	18,7%	18,1%	20,2%
	Males	NR	8	10	11	18	7	3	25	24	23	26
		N	59,5	46,3	22,2	35,9	25,7	65,7	17,4	34,4	33,5	31,9
		MWCV_AGYIM_W	25,8%	22,8%	27,2%	25,3%	25,7%	19,8%	62,2%	15,9%	17,8%	17,5%
		MWCV_AGY_W	28,0%	24,2%	28,2%	26,8%	29,9%	25,2%	63,7%	16,8%	19,3%	18,5%
		MWCV_AGY_U	28,4%	24,8%	28,3%	26,9%	29,1%	25,9%	63,1%	16,9%	19,3%	18,8%
North Coast	Females	NR	1	1				1	1	1	2	1
		N	12,0	26,0				11,0	23,0	8,0	83,0	34,0
		MWCV_AGYIM_W	82,5%	78,3%				103,2%	61,1%	76,2%	34,0%	73,8%
		MWCV_AGY_W	80,9%	84,5%				105,9%	63,2%	75,9%	40,7%	80,5%
		MWCV_AGY_U	80,7%	86,5%				108,4%	63,4%	75,7%	41,1%	80,0%
	Males	NR	1	1				1	1	1	2	1
		N	11,0	43,0				17,0	19,0	7,0	80,0	14,0
		MWCV_AGYIM_W	91,4%	64,4%				79,4%	78,8%	89,7%	36,9%	97,5%
		MWCV_AGY_W	95,8%	72,5%				84,8%	80,1%	93,2%	45,4%	100,7%
		MWCV_AGY_U	92,5%	72,3%				82,7%	78,2%	90,0%	45,7%	100,4%
Orkney	Females	NR	27	23	16	25	18	33	17	56	173	201
		N	15,6	11,3	7,6	14,0	18,4	18,5	8,5	10,3	11,1	9,5
		MWCV_AGYIM_W	24,4%	26,7%	31,5%	21,1%	20,9%	22,6%	27,1%	19,9%	7,9%	10,2%
		MWCV_AGY_W	24,6%	26,7%	32,3%	22,3%	21,6%	23,1%	27,2%	20,3%	8,2%	10,5%
		MWCV_AGY_U	25,0%	26,8%	32,2%	22,0%	21,4%	23,2%	26,8%	20,1%	8,3%	10,5%
	Males	NR	28	24	16	25	18	33	16	55	167	202
		N	12,5	8,5	10,3	15,6	17,9	21,8	12,1	8,7	10,8	8,4
		MWCV_AGYIM_W	25,7%	32,0%	32,0%	30,8%	20,9%	23,0%	30,0%	17,8%	8,6%	9,7%
		MWCV_AGY_W	26,1%	32,0%	32,6%	31,1%	21,9%	24,0%	31,7%	18,4%	8,9%	9,8%
		MWCV_AGY_U	25,9%	32,2%	32,3%	31,3%	22,1%	23,8%	31,1%	18,4%	8,9%	10,0%

Table 10.14 MWCV estimates for lobster for all areas except Shetland, for the existing sampling regimes 2007 to 2016 *continuation of previous table.*

Management Area	Gender	Variable	Year								
			2007	2008	2009	2010	2011	2012	2013	2014	2016
Papa Bank	Females	NR				2	4	1	2	3	2
		N				76,5	28,0	85,0	50,5	46,0	22,5
		MWCV_AGYIM_W				38,7%	39,2%	48,2%	49,5%	49,4%	56,5%
		MWCV_AGY_W				44,2%	41,0%	59,7%	56,3%	52,7%	62,0%
		MWCV_AGY_U				44,5%	40,8%	61,1%	58,9%	52,8%	65,8%
	Males	NR				2	4	1	2	3	3
		N				87,0	17,5	104,0	44,0	36,0	13,5
		MWCV_AGYIM_W				36,0%	34,0%	44,3%	53,1%	44,5%	70,8%
		MWCV_AGY_W				44,4%	34,3%	55,3%	57,5%	47,8%	73,7%
		MWCV_AGY_U				45,5%	36,2%	56,1%	59,2%	47,8%	58,0%
South East	Females	NR	21	23	17	18	15	21	26	65	31
		N	8,9	8,5	6,4	7,6	8,7	6,0	18,8	15,3	12,1
		MWCV_AGYIM_W	15,0%	25,3%	29,4%	16,0%	23,1%	23,1%	16,9%	11,5%	13,5%
		MWCV_AGY_W	15,5%	26,8%	30,7%	16,9%	23,4%	23,5%	17,9%	11,7%	14,1%
		MWCV_AGY_U	15,5%	27,1%	31,2%	16,8%	23,6%	23,4%	18,7%	11,9%	14,0%
	Males	NR	22	23	15	19	14	21	26	66	43
		N	7,5	10,1	9,1	10,9	9,5	7,4	8,4	10,7	13,5
		MWCV_AGYIM_W	18,4%	25,1%	28,8%	17,1%	15,1%	19,8%	25,5%	12,1%	13,8%
		MWCV_AGY_W	19,1%	30,8%	29,8%	17,9%	15,6%	20,8%	25,8%	12,4%	16,4%
		MWCV_AGY_U	19,1%	31,3%	30,9%	18,3%	15,6%	20,8%	26,9%	12,4%	16,7%
South Minch	Females	NR	2	6	6	5	8	9	15	10	15
		N	14,0	5,3	10,2	7,2	19,3	8,8	8,3	5,6	11,2
		MWCV_AGYIM_W	49,5%	38,7%	33,5%	40,0%	32,9%	26,8%	27,2%	29,6%	26,6%
		MWCV_AGY_W	51,9%	39,5%	35,1%	40,9%	34,3%	27,2%	27,5%	30,4%	28,3%
		MWCV_AGY_U	51,2%	38,5%	34,1%	41,1%	33,4%	28,3%	27,8%	30,3%	28,7%
	Males	NR	2	6	6	5	8	9	16	10	9
		N	23,0	10,3	19,7	10,6	27,6	14,3	10,2	8,1	16,9
		MWCV_AGYIM_W	48,4%	31,9%	30,7%	48,7%	36,0%	34,3%	30,4%	28,9%	31,4%
		MWCV_AGY_W	52,2%	33,3%	32,1%	49,4%	36,2%	34,7%	31,0%	29,2%	34,4%
		MWCV_AGY_U	53,4%	33,4%	32,4%	50,0%	35,9%	35,9%	31,4%	29,4%	30,7%
Sule	Females	NR				1	1				
		N				14,0	35,0				
		MWCV_AGYIM_W				73,6%	63,6%				
		MWCV_AGY_W				73,0%	69,0%				
		MWCV_AGY_U				74,6%	70,8%				
	Males	NR				1	1				
		N				18,0	50,0				
		MWCV_AGYIM_W				68,6%	52,1%				
		MWCV_AGY_W				71,4%	58,4%				
		MWCV_AGY_U				69,0%	59,9%				
Ullapool	Females	NR	1						1		
		N	25,0						30,0		
		MWCV_AGYIM_W	65,7%						53,7%		
		MWCV_AGY_W	72,2%						59,2%		
		MWCV_AGY_U	73,5%						61,4%		
	Males	NR	1					1			
		N	56,0					31,0			
		MWCV_AGYIM_W	46,4%					52,5%			
		MWCV_AGY_W	54,9%					56,1%			
		MWCV_AGY_U	55,9%					57,6%			

Table 10.15 MWCV estimates for crab for all areas except Shetland, for the existing sampling regimes 2007 to 2016.

Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	Females	NR	3	3				1	3	1	3	1
		N	41,3	40,3				9,0	15,0	32,0	7,3	39,0
		MWCV_AGYIM_W	54,5%	58,7%				114,7%	57,5%	70,5%	58,6%	73,4%
		MWCV_AGY_W	48,8%	57,4%				116,2%	57,8%	65,7%	57,3%	68,4%
		MWCV_AGY_U	53,8%	59,9%				117,4%	58,3%	67,7%	57,6%	73,6%
	Males	NR	3	3				1	2	1	3	1
		N	109,3	48,0				26,0	36,0	90,0	36,0	124,0
		MWCV_AGYIM_W	47,6%	47,9%				94,6%	67,8%	58,2%	72,5%	54,1%
		MWCV_AGY_W	43,1%	44,9%				91,0%	61,7%	49,0%	71,8%	46,0%
		MWCV_AGY_U	48,0%	47,4%				93,5%	65,5%	60,2%	74,3%	55,4%
East Coast	Females	NR	14	10	25	26	25	35	25	33	30	21
		N	50,1	31,7	93,9	65,5	33,2	81,9	89,2	76,4	72,1	98,2
		MWCV_AGYIM_W	41,6%	37,5%	29,4%	20,5%	27,6%	20,8%	20,4%	15,0%	26,3%	17,3%
		MWCV_AGY_W	40,0%	36,3%	27,7%	18,5%	26,2%	19,7%	18,9%	13,3%	25,8%	16,1%
		MWCV_AGY_U	40,5%	37,5%	29,9%	20,5%	27,3%	20,8%	20,3%	15,1%	26,3%	17,5%
	Males	NR	15	10	25	27	26	35	25	35	32	22
		N	68,6	82,2	41,6	45,7	49,7	95,3	74,4	69,6	73,7	73,8
		MWCV_AGYIM_W	42,6%	31,8%	31,4%	24,5%	20,2%	18,8%	18,8%	18,3%	20,5%	17,5%
		MWCV_AGY_W	40,8%	30,5%	31,0%	22,9%	18,2%	17,1%	17,1%	17,3%	19,4%	16,3%
		MWCV_AGY_U	42,5%	32,0%	32,1%	24,1%	19,9%	18,4%	18,8%	18,4%	20,4%	17,6%
Hebrides	Females	NR	10	10	12	8	10	19	30	20	22	26
		N	83,6	176,5	129,2	341,6	394,5	275,3	152,0	362,9	203,1	208,2
		MWCV_AGYIM_W	55,0%	24,9%	23,0%	22,7%	20,2%	15,0%	19,6%	16,1%	26,0%	15,4%
		MWCV_AGY_W	53,1%	20,8%	20,9%	20,4%	17,6%	12,3%	17,7%	13,7%	23,5%	12,6%
		MWCV_AGY_U	56,0%	24,3%	22,9%	22,9%	20,5%	14,8%	20,0%	16,1%	25,8%	15,6%
	Males	NR	10	10	11	8	10	19	30	21	24	26
		N	36,5	100,1	46,0	68,9	46,5	54,7	45,8	70,9	58,6	81,3
		MWCV_AGYIM_W	69,3%	26,2%	34,8%	37,3%	42,6%	31,5%	26,5%	23,9%	26,5%	20,7%
		MWCV_AGY_W	68,7%	21,7%	33,3%	35,1%	41,3%	30,1%	24,1%	21,4%	25,6%	17,6%
		MWCV_AGY_U	70,5%	25,1%	34,8%	37,9%	42,8%	31,8%	26,4%	23,9%	27,1%	20,6%
North Coast	Females	NR	1	2	2			3	3	1	2	11
		N	80,0	361,5	412,0			335,0	257,7	594,0	384,0	753,5
		MWCV_AGYIM_W	52,7%	39,7%	32,8%			24,3%	29,7%	37,6%	36,3%	13,3%
		MWCV_AGY_W	44,4%	32,1%	27,7%			19,8%	24,4%	31,0%	29,5%	10,7%
		MWCV_AGY_U	51,3%	39,5%	33,8%			24,5%	29,5%	38,0%	37,1%	13,2%
	Males	NR	1	2	2			3	3	1	2	11
		N	20,0	60,5	38,0			83,7	212,0	434,0	318,5	77,4
		MWCV_AGYIM_W	88,3%	47,5%	70,3%			38,2%	32,2%	43,6%	39,3%	21,4%
		MWCV_AGY_W	90,4%	42,2%	65,4%			34,4%	25,8%	36,6%	32,7%	19,1%
		MWCV_AGY_U	91,5%	48,7%	69,0%			37,8%	31,1%	43,4%	39,8%	21,7%
Orkney	Females	NR	15	19	17	58	41	57	110	158	323	401
		N	76,3	87,2	66,6	46,4	69,1	63,5	113,0	38,0	59,5	100,3
		MWCV_AGYIM_W	34,0%	27,7%	28,3%	16,7%	20,7%	22,7%	12,9%	14,8%	8,1%	7,8%
		MWCV_AGY_W	32,0%	26,3%	27,0%	15,7%	19,6%	21,7%	12,0%	14,4%	7,6%	7,6%
		MWCV_AGY_U	33,6%	27,9%	28,3%	16,7%	20,9%	22,6%	12,9%	14,6%	8,1%	7,8%
	Males	NR	15	19	18	77	46	70	134	186	381	454
		N	55,9	59,6	73,9	73,0	67,1	90,9	93,8	81,2	73,2	72,9
		MWCV_AGYIM_W	28,2%	31,1%	21,7%	14,3%	15,5%	16,2%	11,8%	8,1%	6,0%	5,0%
		MWCV_AGY_W	26,4%	28,8%	20,1%	13,4%	14,7%	15,4%	11,4%	7,5%	5,5%	4,6%
		MWCV_AGY_U	28,1%	31,2%	21,7%	14,4%	15,5%	16,3%	12,1%	8,1%	6,0%	5,0%

Table 10.16 MWCV estimates for crab for all areas except Shetland, for the existing sampling regimes 2007 to 2016, continuation of previous table.

Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Papa Bank	Females	NR			1	2	3	1	4	3	2	4
		N			1079,0	1795,0	1129,0	609,0	938,0	1347,3	1277,5	1269,0
		MWCV_AGYIM_W			37,0%	32,5%	26,1%	40,8%	27,6%	26,4%	28,2%	22,4%
		MWCV_AGY_W			30,2%	25,8%	21,1%	33,2%	22,1%	21,5%	23,6%	18,3%
		MWCV_AGY_U			36,5%	31,6%	26,3%	40,5%	27,3%	26,4%	28,8%	22,7%
	Males	NR			1	2	3	1	4	3	2	4
		N			241,0	166,0	385,7	137,0	191,8	219,0	548,0	270,8
		MWCV_AGYIM_W			38,6%	37,1%	25,8%	50,2%	39,2%	28,6%	28,5%	27,9%
		MWCV_AGY_W			32,1%	30,4%	21,1%	42,3%	35,4%	24,2%	23,8%	24,1%
		MWCV_AGY_U			38,1%	37,3%	25,5%	49,9%	38,7%	28,5%	28,8%	28,0%
South East	Females	NR	19	40	28	24	22	33	37	41	26	18
		N	10,4	13,8	25,5	16,2	9,0	11,5	27,0	22,8	21,0	27,7
		MWCV_AGYIM_W	43,5%	22,3%	25,4%	30,3%	28,8%	24,9%	23,3%	25,2%	25,1%	31,6%
		MWCV_AGY_W	43,2%	21,7%	24,7%	29,6%	27,7%	24,2%	22,4%	24,4%	24,5%	31,0%
		MWCV_AGY_U	43,5%	22,3%	25,5%	30,5%	28,4%	24,8%	23,4%	24,9%	24,7%	31,8%
	Males	NR	20	42	28	25	22	33	45	41	43	19
		N	39,1	54,0	51,9	36,1	23,7	45,3	49,7	70,4	55,7	44,3
		MWCV_AGYIM_W	28,7%	14,3%	17,8%	19,5%	22,5%	20,5%	15,4%	14,9%	18,6%	27,2%
		MWCV_AGY_W	26,5%	13,5%	16,9%	18,1%	21,8%	19,7%	14,7%	13,9%	18,0%	26,3%
		MWCV_AGY_U	28,6%	14,3%	18,0%	19,4%	22,6%	20,3%	15,4%	15,1%	18,7%	27,4%
South Minch	Females	NR	2	7	6	6	7	6	12	7	5	6
		N	28,5	48,7	48,0	53,2	135,0	86,8	29,5	37,6	63,6	30,5
		MWCV_AGYIM_W	77,3%	37,9%	57,2%	35,2%	80,6%	29,5%	51,9%	34,2%	52,0%	36,1%
		MWCV_AGY_W	73,2%	35,4%	53,2%	32,4%	76,3%	26,2%	50,4%	30,4%	50,7%	33,6%
		MWCV_AGY_U	77,9%	38,7%	56,1%	35,7%	79,1%	29,6%	51,0%	34,4%	52,5%	35,4%
	Males	NR	2	7	5	6	7	6	13	8	7	6
		N	47,5	35,7	57,0	83,5	40,6	74,2	35,2	22,3	47,3	39,0
		MWCV_AGYIM_W	62,7%	51,1%	61,7%	36,1%	77,7%	57,4%	40,7%	55,3%	37,0%	43,7%
		MWCV_AGY_W	60,5%	50,4%	60,3%	33,1%	74,7%	54,2%	39,9%	54,0%	33,0%	41,5%
		MWCV_AGY_U	64,3%	52,1%	63,1%	35,7%	75,9%	55,0%	41,0%	55,3%	36,5%	42,9%
Sule	Females	NR	2	3	3	14	3	17	9	2		10
		N	895,5	239,7	659,0	373,2	472,7	426,2	931,4	622,5		1203,0
		MWCV_AGYIM_W	34,7%	43,3%	32,1%	17,2%	33,8%	14,8%	19,9%	31,5%		15,9%
		MWCV_AGY_W	28,3%	37,7%	26,0%	14,4%	28,4%	13,0%	16,2%	25,4%		12,7%
		MWCV_AGY_U	34,7%	43,4%	32,8%	17,2%	33,7%	14,7%	19,9%	31,7%		15,6%
	Males	NR	3	3	3	14	2	17	9	2		10
		N	667,0	49,7	127,3	36,4	61,5	195,8	97,2	31,5		89,5
		MWCV_AGYIM_W	43,4%	69,6%	37,9%	34,9%	63,3%	17,5%	37,1%	65,3%		28,3%
		MWCV_AGY_W	37,8%	67,2%	31,4%	33,5%	60,2%	15,2%	34,5%	64,3%		27,1%
		MWCV_AGY_U	44,1%	70,5%	38,3%	34,8%	63,7%	17,4%	37,5%	66,4%		28,6%
Ullapool	Females	NR			1		1		2	2		3
		N			173,0		95,0		81,0	61,5		76,0
		MWCV_AGYIM_W			47,4%		61,3%		50,5%	65,0%		54,7%
		MWCV_AGY_W			38,9%		54,1%		45,0%	59,9%		51,0%
		MWCV_AGY_U			46,9%		62,3%		51,1%	66,9%		55,1%
	Males	NR			1		1		2	2		3
		N			21,0		57,0		12,0	32,0		113,3
		MWCV_AGYIM_W			93,0%		60,3%		90,3%	59,1%		46,5%
		MWCV_AGY_W			92,3%		53,7%		87,9%	57,6%		43,2%
		MWCV_AGY_U			94,0%		59,9%		91,8%	60,9%		47,6%

Table 10.17 MWCV estimates for scallops for all areas except the Irish Sea, for the existing sampling regimes 2007 to 2016.

Management Area	Variable	Year									
		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	NR	2	1	0	0	1	1	1	5	2	3
	N	117,5	168,0	0,0	0,0	123,0	96,0	146,0	124,8	262,0	178,3
	MWCV_AYMI_W	43,2%	0,0%	0,0%	0,0%	52,0%	0,0%	60,4%	29,2%	44,6%	36,0%
	MWCV_AY_W	43,9%	0,0%	0,0%	0,0%	52,7%	0,0%	61,8%	29,9%	45,1%	35,7%
East Coast	NR	18,0	17	12	6	5	11	14	6	12	10
	N	226,2	232,7	252,9	211,2	245,2	195,2	202,7	238,2	214,7	198,3
	MWCV_AYMI_W	17,7%	14,5%	19,8%	22,4%	27,1%	19,8%	21,1%	24,2%	20,8%	25,0%
	MWCV_AY_W	18,3%	14,6%	20,1%	22,9%	27,3%	20,0%	21,3%	24,8%	21,5%	25,1%
North East	NR	4	21	7	6	4	10	10	5	5	12
	N	232,5	207,0	221,4	225,2	184,3	212,0	169,4	230,0	249,8	211,3
	MWCV_AYMI_W	26,7%	17,7%	23,3%	31,4%	30,2%	20,4%	24,2%	26,4%	30,3%	17,9%
	MWCV_AY_W	28,0%	18,3%	23,6%	32,6%	30,7%	20,9%	24,5%	27,4%	30,6%	18,3%
North West	NR	17	13	15	31	16	27	33	21	42	22
	N	240,7	223,0	237,4	163,9	144,1	210,3	178,8	179,9	168,0	176,8
	MWCV_AYMI_W	16,7%	21,1%	17,5%	17,1%	20,4%	13,9%	12,4%	15,2%	11,3%	17,2%
	MWCV_AY_W	17,2%	21,4%	17,6%	17,2%	20,8%	14,1%	12,7%	15,2%	11,6%	17,8%
Orkney	NR	3	6	8	9	5	6	3	2	4	3
	N	188,0	177,8	136,1	138,0	168,2	122,8	170,7	226,5	189,8	182,0
	MWCV_AYMI_W	38,1%	31,0%	25,1%	24,1%	27,5%	35,6%	45,4%	40,4%	33,4%	30,3%
	MWCV_AY_W	39,0%	30,7%	25,6%	24,0%	27,4%	35,7%	45,2%	40,6%	33,7%	30,7%
Shetland	NR	110	94	59	65	65	68	70	64	71	72
	N	106,2	106,0	100,6	99,8	94,4	99,3	99,0	100,1	97,8	98,7
	MWCV_AYMI_W	7,1%	8,0%	8,8%	8,9%	8,7%	9,1%	9,7%	9,1%	8,1%	8,5%
	MWCV_AY_W	7,2%	8,0%	8,8%	8,9%	8,7%	9,2%	9,9%	9,2%	8,2%	8,4%
WoK	NR	24	30	30	21	15	33	36	49	43	36
	N	182,0	183,2	211,9	221,0	175,1	193,5	178,3	158,7	171,0	142,5
	MWCV_AYMI_W	12,6%	11,4%	12,0%	12,9%	14,9%	11,7%	11,6%	15,1%	9,9%	11,5%
	MWCV_AY_W	13,0%	11,7%	12,2%	13,1%	15,2%	12,0%	11,8%	15,5%	10,1%	11,8%

Table 10.18 An assessment of whether biological sampling for lobster and crab lengths has attained either a 20% or a 30% MWCV threshold over the last five years.

Lobster Length frequency sampling, Meeting 20% or 30% MWCV thresholds			Crab Length frequency sampling, Meeting 20% or 30% MWCV thresholds			
		20%	30%		20%	30%
Clyde	Females	No	No	Clyde	No	No
	Males	No	No		No	No
East Coast	Females	No	Yes	East Coast	Yes	Yes
	Males	No	Yes		Yes	Yes
Hebrides	Females	Yes	Yes	Hebrides	Yes	Yes
	Males	Yes	Yes		No	Yes
North Coast	Females	No	No	North Coast 2016 only	Yes	Yes
	Males	No	No		Yes	Yes
Orkney	Females	Yes	Yes	Orkney	Yes	Yes
	Males	Yes	Yes		Yes	Yes
Papa	Females	No	No	Papa	No	Yes
	Males	No	No		No	Yes
SE	Females	Yes	Yes	SE	No	Yes
	Males	Yes	Yes		Yes	Yes
South Minch	Females	No	Yes	South Minch	No	No
	Males	No	No		No	No
Sule	Females	No	No	Sule	Yes	Yes
	Males	No	No		No	No
Ullapool	Females	No	No	Ullapool	No	No
	Males	No	No		No	No

Table 10.19 An assessment of whether biological sampling for scallop lengths has attained either a 20% or a 30% MWCV threshold over the last five years.

Scallop Length frequency sampling, Meeting 20% or 30% MWCV thresholds		
	20%	30%
Clyde	No	No
East Coast	No	Yes
North East	No	Yes
North West	Yes	Yes
Orkney	No	No
Shetland	Yes	Yes
WoK	Yes	Yes

Table 10.20 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for lobster, using the variance components where month and statistical variance components are calculated in GLMER, and the weighted/unweighted cases where the month and statistical area variance components are not estimated. Simple random sampling assumed. Highlighted regions are judged to be undesirable, i.e. MWCV >30%, based loosely on Technical Appendix 3 results which simulated the link between MWCV and LCA based fishing mortality estimates.

		Number of Fish Sampled Per Trip: Var Components exclude month and statistical area variance					
		1	10	20	30	100	200
Number of Trips Sampled	1	119%	77%	59%	47%	34%	34%
	3	68%	45%	34%	27%	19%	19%
	5	53%	35%	26%	22%	15%	15%
	10	38%	25%	19%	15%	11%	11%
	25	24%	16%	12%	10%	7%	7%
	30	22%	14%	11%	9%	6%	6%
	35	20%	14%	10%	8%	6%	6%
	40	19%	12%	9%	8%	5%	5%
	45	18%	12%	9%	7%	5%	5%

		Number of Fish Sampled Per Trip: Var Components include month and statistical area variance, weighted GLMER					
		1	10	20	30	100	200
Number of Trips Sampled	1	125%	80%	62%	52%	41%	42%
	3	71%	46%	35%	30%	23%	24%
	5	54%	37%	28%	24%	18%	18%
	10	38%	25%	20%	17%	13%	13%
	25	24%	16%	13%	11%	8%	8%
	30	21%	15%	11%	9%	8%	7%
	35	20%	13%	10%	9%	7%	7%
	40	19%	13%	10%	9%	7%	7%
	45	18%	12%	9%	8%	6%	6%

		Number of Fish Sampled Per Trip: Var Components include month and statistical area variance, unweighted GLMER					
		1	10	20	30	100	200
Number of Trips Sampled	1	120%	82%	65%	58%	45%	46%
	3	71%	47%	37%	34%	26%	26%
	5	55%	37%	30%	26%	20%	20%
	10	39%	26%	21%	19%	14%	14%
	25	24%	16%	13%	12%	9%	9%
	30	22%	15%	12%	11%	8%	8%
	35	20%	14%	11%	10%	8%	8%
	40	19%	13%	10%	9%	7%	7%
	45	18%	12%	10%	9%	7%	7%

Table 10.21 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for crab, using the variance components where month and statistical variance components are calculated in GLMER, and the weighted/unweighted cases where the month and statistical area variance components are not estimated. Simple random sampling assumed. Highlighted regions are judged to be undesirable, i.e. MWCV >30%.

		Number of Crab Sampled Per Trip: Var Components exclude month and statistical area variance					
		1	10	20	30	100	200
Number of Trips Sampled	1	181%	149%	111%	90%	62%	61%
	3	103%	84%	66%	52%	35%	37%
	5	81%	66%	50%	42%	27%	28%
	10	56%	47%	36%	30%	20%	20%
	25	37%	30%	23%	19%	12%	12%
	30	32%	26%	20%	17%	11%	11%
	35	31%	25%	19%	15%	11%	11%
	40	28%	23%	17%	15%	10%	10%
	45	27%	21%	16%	14%	9%	10%
		Number of Crab Sampled Per Trip: Var Components include month and statistical area variance, weighted GLMER					
		1	10	20	30	100	200
Number of Trips Sampled	1	176%	150%	112%	88%	55%	55%
	3	105%	84%	64%	51%	31%	31%
	5	79%	65%	50%	41%	25%	25%
	10	55%	46%	35%	28%	18%	18%
	25	36%	28%	22%	18%	11%	11%
	30	33%	26%	21%	16%	10%	10%
	35	29%	25%	18%	15%	9%	9%
	40	28%	23%	18%	14%	9%	9%
	45	26%	21%	17%	13%	8%	8%
		Number of Crab Sampled Per Trip: Var Components include month and statistical area variance, unweighted GLMER					
		1	10	20	30	100	200
Number of Trips Sampled	1	179%	146%	114%	94%	64%	63%
	3	103%	85%	65%	54%	37%	36%
	5	79%	67%	50%	41%	28%	28%
	10	57%	47%	35%	29%	20%	20%
	25	36%	29%	22%	19%	13%	12%
	30	32%	27%	21%	17%	11%	12%
	35	30%	25%	19%	16%	11%	10%
	40	28%	23%	18%	15%	10%	10%
	45	27%	22%	17%	14%	9%	9%

Table 10.22 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for scallops, using the variance components where month and statistical variance components are calculated in GLMER (second panel), and the weighted/unweighted cases where the month and statistical area variance components are not estimated. Simple random sampling assumed. Highlighted regions are judged to be undesirable, i.e. MWCV >30%.

		Number of Scallops Sampled Per Trip: Var Components exclude month and statistical area as variance components in GLMER, weighted GLMER					
		1	10	20	30	100	200
Number of Trips Sampled	1	143%	171%	145%	123%	65%	61%
	3	83%	96%	80%	69%	37%	35%
	5	65%	75%	63%	52%	28%	27%
	10	44%	54%	45%	38%	20%	19%
	25	29%	34%	27%	23%	13%	12%
	30	25%	31%	26%	22%	12%	11%
	35	24%	29%	23%	20%	11%	10%
	40	23%	26%	22%	19%	10.5%	9%
	45	20%	26%	21%	18%	9.8%	9%

		Number of Scallops Sampled Per Trip: Var Components include month and statistical area as variance components in GLMER, weighted GLMER					
		1	10	20	30	100	200
Number of Trips Sampled	1	150%	169%	136%	115%	60%	52%
	3	89%	94%	78%	64%	35%	31%
	5	69%	74%	59%	50%	28%	23%
	10	47%	52%	43%	35%	19%	17%
	25	29%	33%	27%	22%	12%	10%
	30	27%	29%	24%	20%	11%	9%
	35	25%	28%	23%	19%	10%	9%
	40	24%	26%	21%	18%	9.2%	8%
	45	22%	26%	20%	17%	9.1%	8%

Table 10.23 A comparison, for lobster, between the design based MWCV and the empirical based MWCV, using the sample size achieved in 2016. The empirical results are for the results based on error variance from the weighted GLMER model, where the only random effects included were gender (G), year (Y) and assessment area (A). For the designed based results the Nlobsters are the same for each trip whereas in the empirical case Nlobsters varies from trip to trip and the value shown in the table is a mean.

		2016		Design based MWCV	Empirical based MWCV
		Ntrips	Nlobsters		
Clyde	Females	1	10.0	79%	59%
	Males	1	16.0	67%	54%
East Coast	Females	14	5.7	25%	30%
	Males	14	5.6	26%	37%
Hebrides	Females	25	32.9	9%	20%
	Males	26	31.9	9%	19%
North Coast	Females	1	34.0	44%	81%
	Males	1	14.0	69%	101%
Orkney	Females	201	9.5	6%	11%
	Males	202	8.4	6%	10%
Papa	Females	3	27.0	29%	65%
	Males	3	29.3	28%	56%
SE	Females	31	8.2	15%	17%
	Males	30	6.9	16%	16%
South Minch	Females	15	17.1	16%	28%
	Males	15	18.3	16%	31%
Sule	Females				
	Males				
Ullapool	Females				
	Males				

Table 10.24 A comparison, for crab, between the design based MWCV and the empirical based MWCV, using the sample size achieved in 2016. The empirical results are for the results based on error variance from the weighted GLMER model, where the only random effects included were gender (G), year (Y) and assessment area (A). For the designed based results the Ncrabs are the same for each trip whereas in the empirical case Ncrabs varies from trip to trip and the value shown in the table is a mean.

		2016		Design based MWCVs	Empirical based MWCVs
		Ntrips	Ncrabs		
Clyde	Females	1	39.0	81%	68%
	Males	1	124.0	63%	46%
East Coast	Females	21	98.2	14%	16%
	Males	22	73.8	13%	16%
Hebrides	Females	26	208.2	12%	13%
	Males	26	81.3	12%	18%
North Coast	Females	11	753.5	19%	11%
	Males	11	77.4	19%	19%
Orkney	Females	401	100.3	3%	8%
	Males	454	72.9	3%	5%
Papa	Females	4	1269.0	32%	18%
	Males	4	270.8	32%	24%
SE	Females	18	27.7	23%	31%
	Males	19	44.3	17%	26%
outh Mind	Females	6	30.5	37%	34%
	Males	6	39.0	33%	42%
Sule	Females	10	1203.0	19%	13%
	Males	10	89.5	20%	27%
Ullapool	Females	3	76.0	36%	51%
	Males	3	113.3	36%	43%

Table 10.25 A comparison, for scallops, between the design based MWCV and the empirical based MWCV, using the sample size achieved in 2016. The empirical results are for the results based on error variance from the weighted GLMER model, where the only random effects included were year (Y) and assessment area (A). For the designed based results the Nscallopss are the same for each trip whereas in the empirical case Nscallopss varies from trip to trip and the value shown in the table is a mean.

		2016		Design based MWCV	Empirical based MWCV
		Ntrips	Nscallopss		
Clyde		3	178.3	31%	36%
East Coast		10	198.3	17%	25%
North East		12	211.3	15%	18%
North West		22	176.8	12%	18%
Orkney		3	182	31%	31%
Shetland		72	98.7	7%	8%
WoK		36	142.5	9%	12%

Table 10.26 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for lobster, using the variance components where month and statistical area variance components are calculated in the GLMER. Simple random sampling assumed, and the variance of the mean proportions are inflated by an amount that is related to the scale of the M,A variance components in relation to the error variance. Here we assumed that an additional variance amount is added to the variance of the mean which is 2/3 of the “asymptotic” (large sample size) error variance for a single record, averaged over length classes 110, 115, 120 and 125, and multiplied by a balancing factor V (see text) of 0.25. Highlighted regions are judged to be undesirable on the basis of a rough rule of thumb of MWCV >30%. These results need to be compared to those presented in Table 10.22.

		Number of lobster Sampled Per Trip: Ad hoc adjustment to address month and stat area Var Components					
		1	10	20	30	100	200
Number of Trips Sampled	1	124%	80%	59%	48%	35%	35%
	3	69%	47%	35%	30%	21%	21%
	5	54%	36%	27%	23%	17%	17%
	10	39%	26%	20%	17%	13%	13%
	25	26%	18%	14%	12%	10%	10%
	30	24%	16%	13%	12%	10%	10%
	35	22%	16%	12%	11%	10%	10%
	40	21%	15%	12%	11%	9%	9%
	45	20%	14%	11%	10%	9%	9%

Table 10.27 Predicted MWCVs for different combinations of the number of trips sampled and the number of individuals sampled per trip, for scallops, using the variance components where month and statistical area variance components are calculated in the GLMER. Simple random sampling assumed, and the variance of the mean proportions are inflated by an amount that is related to the scale of the M,A variance components in relation to the error variance. Here we assumed that an additional variance amount is added to the variance of the mean which is 2/3 of the “asymptotic” (large sample size) error variance for a single record, averaged over length classes 130, 135, 140 and 145, and multiplied by a balancing factor V (see text) of 0.25 (top panel) and 0.10 (bottom panel). Highlighted regions are judged to be undesirable on the basis of a rough rule of thumb of MWCV >30%. These results need to be compared to those presented in Table 10.22.

		Number of Fish Sampled Per Trip					
		1	10	20	30	100	200
Number of Trips Sampled	1	156%	175%	142%	116%	63%	56%
	3	93%	112%	91%	74%	40%	35%
	5	73%	91%	75%	63%	32%	29%
	10	60%	76%	62%	51%	25%	24%
	25	41%	63%	53%	45%	21%	21%
	30	42%	61%	53%	45%	20%	20%
	35	39%	59%	50%	39%	21%	20%
	40	40%	58%	46%	42%	20.3%	20%
	45	37%	54%	50%	41%	18.8%	19%

		Number of Fish Sampled Per Trip					
		1	10	20	30	100	200
Number of Trips Sampled	1	148%	172%	137%	117%	61%	54%
	3	91%	102%	82%	68%	37%	32%
	5	72%	80%	66%	55%	29%	26%
	10	55%	64%	50%	43%	23%	20%
	25	37%	49%	39%	33%	17%	15%
	30	35%	45%	38%	31%	16%	15%
	35	32%	44%	36%	31%	15%	15%
	40	31%	42%	36%	29%	14.4%	14%
	45	32%	41%	35%	30%	14.2%	14%

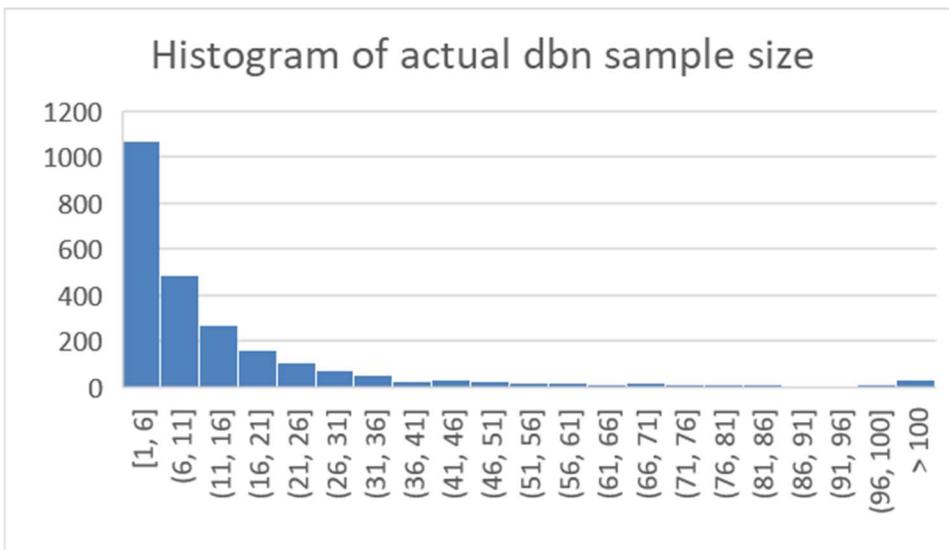


Figure 10.1 A histogram of the number of individuals sampled per trip and gender, over the entire lobster biological sampling dataset.

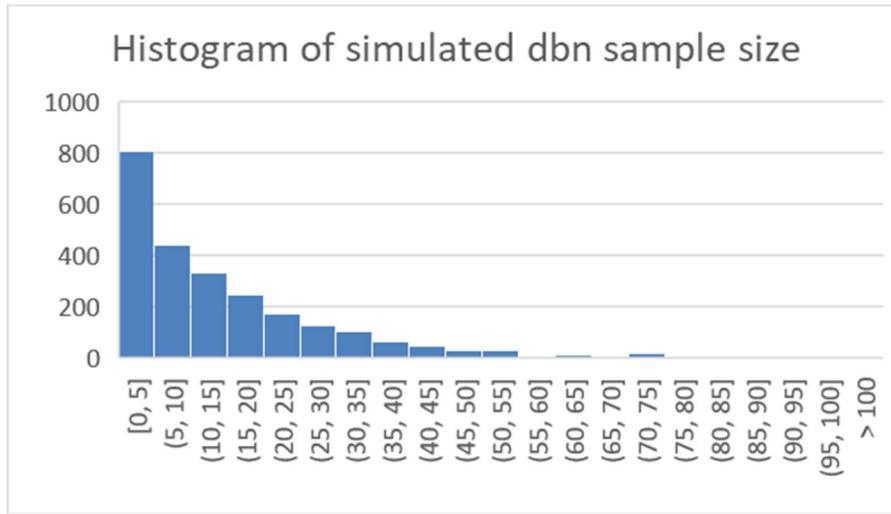


Figure 10.2 A histogram of the number of individuals sampled per trip and gender, for lobster, simulated using an exponential distribution with a mean equal to the empirical mean, subject to the constraint sample size ≥ 1 .

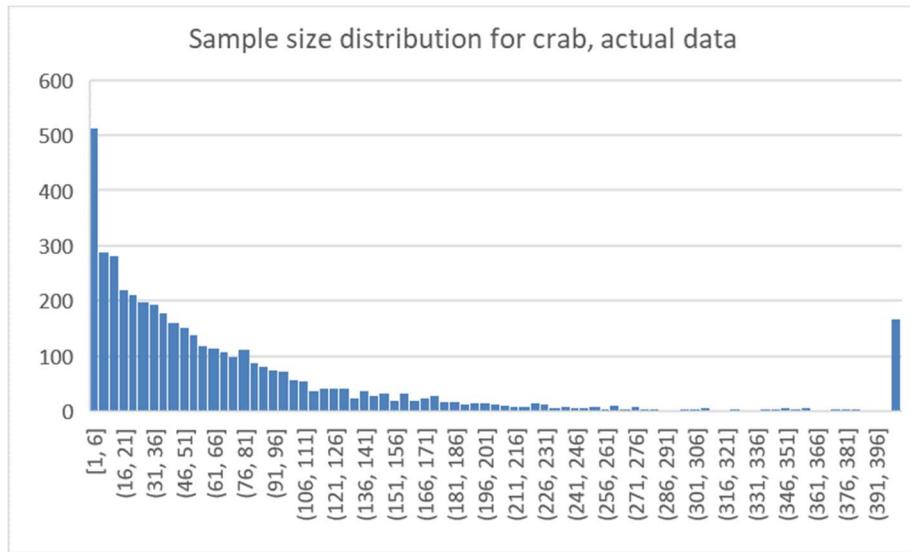


Figure 10.3 A histogram of the number of individuals sampled per trip and gender, over the entire crab biological sampling dataset.

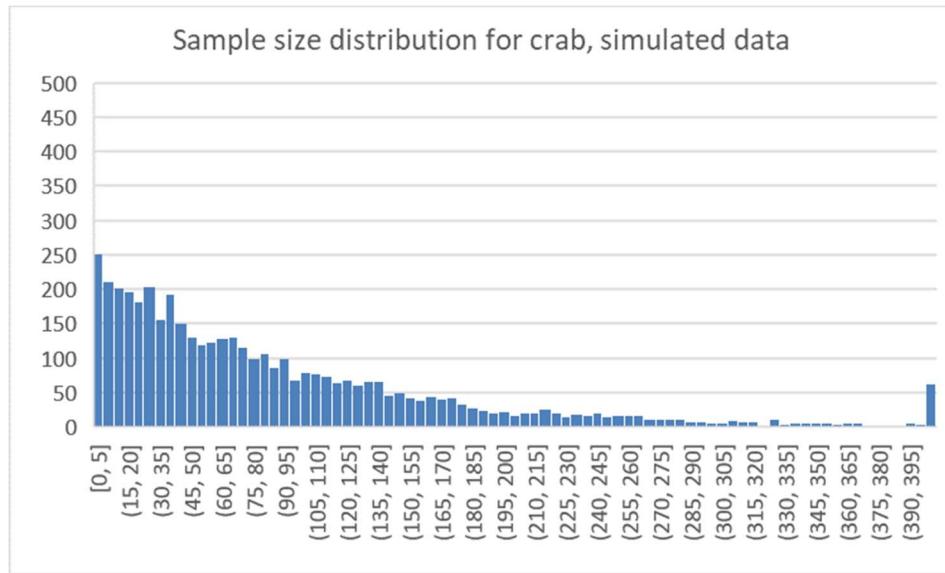


Figure 10.4 A histogram of the number of individuals sampled per trip and gender, for crab, simulated using an exponential distribution with a mean equal to the empirical mean, subject to the constraint sample size ≥ 1 .

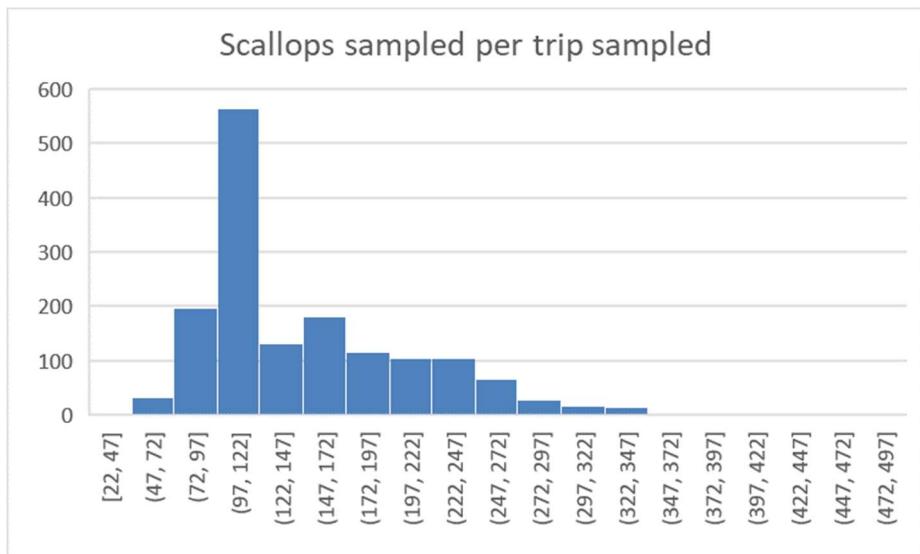


Figure 10.5 A histogram of the number of individuals sampled per trip and gender, over the entire scallop biological sampling dataset.

Table 10.28 Adjusted empirical MWCV estimates for lobster for all areas except Shetland, using double the number of trips compared to the number in the raw data. These results use the version of the GLMER which contains as random effect gender, statistical area, month, season, assessment area and year.

Glmer(AGYMIS) Weighted Lobster LogitBias Corrected Doubled Trip Count MWCV Summary												
Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	Females	NR	2	2	2	2		4	6	2	6	2
		N	2,0	17,0	10,0	13,0		7,5	14,3	2,0	7,3	10,0
		MWCV	34,9%	54,3%	35,4%	43,9%		42,0%	42,2%	57,0%	27,1%	40,4%
	Males	NR	2	2	2	2		4	6	2	6	2
		N	2,0	24,0	24,0	15,0		12,5	11,0	0,0	9,0	16,0
		MWCV	53,0%	51,1%	29,7%	59,3%		41,5%	42,4%	22,3%	32,8%	36,4%
East Coast	Females	NR	14	14	18	24	22	32	34	38	22	28
		N	20,0	14,6	6,0	4,8	10,6	16,4	11,8	14,4	8,3	5,7
		MWCV	22,6%	19,6%	24,9%	21,2%	15,7%	13,9%	27,6%	11,5%	20,0%	20,4%
	Males	NR	14	14	24	24	26	32	34	40	22	28
		N	20,6	22,1	11,8	13,1	16,6	20,3	10,2	22,4	8,9	5,6
		MWCV	20,5%	18,7%	15,0%	24,8%	20,9%	17,4%	25,5%	13,5%	21,6%	25,2%
Hebrides	Females	NR	16	20	22	32	14	6	46	46	46	50
		N	45,1	50,0	21,4	43,6	20,4	45,0	14,3	33,8	30,6	32,9
		MWCV	14,2%	16,7%	17,8%	16,1%	22,4%	13,2%	16,7%	12,6%	11,7%	13,4%
	Males	NR	16	20	22	36	14	6	50	48	46	52
		N	59,5	46,3	22,2	35,9	25,7	65,7	17,4	34,4	33,5	31,9
		MWCV	18,2%	16,1%	19,2%	17,9%	18,1%	14,0%	44,0%	11,2%	12,6%	12,4%
North Coast	Females	NR	2	2				2	2	2	4	2
		N	12,0	26,0				11,0	23,0	8,0	83,0	34,0
		MWCV	58,3%	55,4%				73,0%	43,2%	53,9%	24,1%	52,2%
	Males	NR	2	2				2	2	2	4	2
		N	11,0	43,0				17,0	19,0	7,0	80,0	14,0
		MWCV	64,6%	45,5%				56,2%	55,7%	63,4%	26,1%	69,0%
Orkney	Females	NR	54	46	32	50	36	66	34	112	346	402
		N	15,6	11,3	7,6	14,0	18,4	18,5	8,5	10,3	11,1	9,5
		MWCV	17,3%	18,9%	22,3%	14,9%	14,8%	16,0%	19,2%	14,1%	5,6%	7,2%
	Males	NR	56	48	32	50	36	66	32	110	334	404
		N	12,5	8,5	10,3	15,6	17,9	21,8	12,1	8,7	10,8	8,4
		MWCV	18,2%	22,6%	22,6%	21,7%	14,8%	16,3%	21,2%	12,6%	6,1%	6,9%
Papa Bank	Females	NR				4	8	2	4	6	4	6
		N				76,5	28,0	85,0	50,5	46,0	22,5	27,0
		MWCV				27,4%	27,7%	34,1%	35,0%	34,9%	40,0%	42,0%
	Males	NR				4	8	2	4	6	4	6
		N				87,0	17,5	104,0	44,0	36,0	13,5	29,3
		MWCV				25,5%	24,0%	31,3%	37,6%	31,5%	50,0%	35,8%
South East	Females	NR	42	46	34	36	30	42	52	130	86	62
		N	8,9	8,5	6,4	7,6	8,7	6,0	18,8	15,3	12,1	8,2
		MWCV	10,6%	17,9%	20,8%	11,3%	16,3%	16,3%	12,0%	8,1%	9,5%	11,7%
	Males	NR	44	46	30	38	28	42	52	132	86	60
		N	7,5	10,1	9,1	10,9	9,5	7,4	8,4	10,7	13,5	6,9
		MWCV	13,0%	17,8%	20,3%	12,1%	10,7%	14,0%	18,0%	8,6%	9,7%	11,4%
South Minch	Females	NR	4	12	12	10	16	18	30	20	20	30
		N	14,0	5,3	10,2	7,2	19,3	8,8	8,3	5,6	11,2	17,1
		MWCV	35,0%	27,3%	23,7%	28,3%	23,2%	18,9%	19,2%	21,0%	18,8%	18,8%
	Males	NR	4	12	12	10	16	18	32	20	18	30
		N	23,0	10,3	19,7	10,6	27,6	14,3	10,2	8,1	16,9	18,3
		MWCV	34,2%	22,5%	21,7%	34,4%	25,4%	24,3%	21,5%	20,4%	22,2%	20,9%
Sule	Females	NR				2	2					
		N				14,0	35,0					
		MWCV				52,0%	44,9%					
	Males	NR				2	2					
		N				18,0	50,0					
		MWCV				48,5%	36,8%					
Ullapool	Females	NR	2					2				
		N	25,0						30,0			
		MWCV	46,5%						38,0%			
	Males	NR	2					2				
		N	56,0						31,0			
		MWCV	32,8%						37,1%			

Table 10.29 Adjusted empirical MWCV estimates for lobster for all areas except Shetland, using double the sample size per record compared to the number in the raw data. These results use the version of the GLMER which contains as random effect gender, statistical area, month, season, assessment area and year.

Glmer(AGYMIS) Weighted Lobster LogitBias Corrected Doubled No. Sampled MWCV Summary												
Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	Females	NR	1	1	1	1		2	3	1	3	1
		N	4,0	34,0	20,0	26,0		15,0	28,7	4,0	14,7	20,0
		MWCV	42,0%	58,2%	32,7%	44,7%		46,6%	45,9%	74,7%	31,2%	41,9%
	Males	NR	1	1	1	1		2	3	1	3	1
		N	4,0	48,0	48,0	30,0		25,0	22,0	0,0	18,0	32,0
		MWCV	66,3%	55,7%	31,0%	65,3%		44,1%	45,8%	32,9%	36,0%	35,9%
East Coast	Females	NR	7	7	9	12	11	16	17	19	11	14
		N	40,0	29,1	12,0	9,7	21,3	32,9	23,5	28,7	16,5	11,4
		MWCV	25,5%	21,6%	26,4%	24,3%	19,3%	16,1%	31,1%	13,5%	22,0%	22,5%
	Males	NR	7	7	12	12	13	16	17	20	11	14
		N	41,1	44,3	23,5	26,2	33,2	40,6	20,4	44,7	17,8	11,1
		MWCV	24,6%	20,5%	16,2%	27,8%	24,0%	19,9%	27,7%	17,4%	23,7%	28,7%
Hebrides	Females	NR	8	10	11	16	7	3	23	23	23	25
		N	90,3	100,0	42,7	87,3	40,9	90,0	28,7	67,7	61,2	65,8
		MWCV	16,9%	19,5%	20,0%	17,8%	28,1%	18,7%	17,7%	14,8%	13,7%	15,7%
	Males	NR	8	10	11	18	7	3	25	24	23	26
		N	119,0	92,6	44,4	71,8	51,4	131,3	34,9	68,8	67,0	63,8
		MWCV	20,4%	19,4%	22,4%	20,3%	23,9%	19,5%	56,5%	13,3%	15,2%	14,3%
North Coast	Females	NR	1	1				1	1	1	2	1
		N	24,0	52,0				22,0	46,0	16,0	166,0	68,0
		MWCV	61,3%	57,6%				85,5%	44,3%	62,2%	31,0%	49,8%
	Males	NR	1	1				1	1	1	2	1
		N	22,0	86,0				34,0	38,0	14,0	160,0	28,0
		MWCV	74,9%	49,5%				66,3%	61,1%	75,1%	35,4%	82,7%
Orkney	Females	NR	27	23	16	25	18	33	17	56	173	201
		N	31,1	22,7	15,3	27,9	36,9	37,1	17,1	20,5	22,3	19,1
		MWCV	20,3%	22,7%	25,9%	16,9%	16,3%	17,4%	22,6%	15,8%	6,7%	8,6%
	Males	NR	28	24	16	25	18	33	16	55	167	202
		N	25,0	17,1	20,5	31,3	35,8	43,6	24,3	17,3	21,6	16,8
		MWCV	20,9%	27,2%	27,0%	24,7%	16,9%	19,8%	24,8%	14,2%	7,1%	8,0%
Papa Bank	Females	NR				2	4	1	2	3	2	3
		N				153,0	56,0	170,0	101,0	92,0	45,0	54,0
		MWCV				35,0%	30,4%	46,4%	38,1%	34,1%	42,5%	43,6%
	Males	NR				2	4	1	2	3	2	3
		N				174,0	35,0	208,0	88,0	72,0	27,0	58,7
		MWCV				35,9%	30,2%	43,9%	38,0%	33,1%	55,0%	37,9%
South East	Females	NR	21	23	17	18	15	21	26	65	43	31
		N	17,7	17,0	12,8	15,1	17,5	11,9	37,5	30,5	24,3	16,5
		MWCV	12,2%	20,2%	22,4%	12,6%	20,6%	19,2%	12,4%	9,3%	10,4%	13,5%
	Males	NR	22	23	15	19	14	21	26	66	43	30
		N	15,0	20,2	18,3	21,9	19,0	14,8	16,8	21,5	26,9	13,8
		MWCV	14,7%	24,8%	22,9%	14,6%	11,2%	15,0%	21,5%	9,5%	11,2%	13,4%
South Minch	Females	NR	2	6	6	5	8	9	15	10	10	15
		N	28,0	10,7	20,3	14,4	38,5	17,6	16,5	11,2	22,4	34,3
		MWCV	37,9%	29,6%	27,2%	30,4%	23,4%	22,5%	20,5%	23,4%	22,8%	22,6%
	Males	NR	2	6	6	5	8	9	16	10	9	15
		N	46,0	20,7	39,3	21,2	55,3	28,7	20,4	16,2	33,8	36,7
		MWCV	35,9%	24,5%	25,0%	38,1%	24,6%	27,2%	23,5%	22,7%	26,7%	25,4%
Sule	Females	NR				1	1					
		N				28,0	70,0					
		MWCV				57,7%	45,6%					
	Males	NR				1	1					
		N				36,0	100,0					
		MWCV				50,7%	43,2%					
Ullapool	Females	NR	1						1			
		N	50,0						60,0			
		MWCV	49,6%						40,0%			
	Males	NR	1						1			
		N	112,0						62,0			
		MWCV	39,2%						38,1%			

Table 10.30 Adjusted empirical MWCV estimates for crab for all areas except Shetland, using double the number of trips compared to the number in the raw data. These results use the version of the GLMER which contains as random effect gender, statistical area, month, assessment area and year.

Gimer(AGYMI) Unweighted Crab LogitBias Corrected Doubled Trip Count MWCV Summary

Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	Females	NR	6	6				2	6	2	6	2
		N	41,3	40,3				9,0	15,0	32,0	7,3	39,0
		MWCV	38,6%	41,5%				81,1%	40,6%	49,8%	41,4%	51,9%
	Males	NR	6	6				2	4	2	6	2
		N	109,3	48,0				26,0	36,0	90,0	36,0	124,0
		MWCV	33,7%	33,8%				66,9%	47,9%	41,1%	51,3%	38,3%
East Coast	Females	NR	28	20	50	52	50	70	50	66	60	42
		N	50,1	31,7	93,9	65,5	33,2	81,9	89,2	76,4	72,1	98,2
		MWCV	29,4%	26,5%	20,8%	14,5%	19,5%	14,7%	14,4%	10,6%	18,6%	12,3%
	Males	NR	30	20	50	54	52	70	50	70	64	44
		N	68,6	82,2	41,6	45,7	49,7	95,3	74,4	69,6	73,7	73,8
		MWCV	30,1%	22,5%	22,2%	17,3%	14,3%	13,3%	13,3%	12,9%	14,5%	12,4%
Hebrides	Females	NR	20	20	24	16	20	38	60	40	44	52
		N	83,6	176,5	129,2	341,6	394,5	275,3	152,0	362,9	203,1	208,2
		MWCV	38,9%	17,6%	16,3%	16,0%	14,3%	10,6%	13,9%	11,4%	18,4%	10,9%
	Males	NR	20	20	22	16	20	38	60	42	48	52
		N	36,5	100,1	46,0	68,9	46,5	54,7	45,8	70,9	58,6	81,3
		MWCV	49,0%	18,5%	24,6%	26,4%	30,2%	22,2%	18,7%	16,9%	18,8%	14,6%
North Coast	Females	NR	2	4	4			6	6	2	4	22
		N	80,0	361,5	412,0			335,0	257,7	594,0	384,0	753,5
		MWCV	37,2%	28,1%	23,2%			17,2%	21,0%	26,6%	25,7%	9,4%
	Males	NR	2	4	4			6	6	2	4	22
		N	20,0	60,5	38,0			83,7	212,0	434,0	318,5	77,4
		MWCV	62,4%	33,6%	49,7%			27,0%	22,7%	30,9%	27,8%	15,1%
Orkney	Females	NR	30	38	34	116	82	114	220	316	646	802
		N	76,3	87,2	66,6	46,4	69,1	63,5	113,0	38,0	59,5	100,3
		MWCV	24,0%	19,6%	20,0%	11,8%	14,6%	16,1%	9,1%	10,4%	5,7%	5,5%
	Males	NR	30	38	36	154	92	140	268	372	762	908
		N	55,9	59,6	73,9	73,0	67,1	90,9	93,8	81,2	73,2	72,9
		MWCV	20,0%	22,0%	15,3%	10,1%	11,0%	11,5%	8,4%	5,7%	4,3%	3,5%
Papa Bank	Females	NR			2	4	6	2	8	6	4	8
		N			1079,0	1795,0	1129,0	609,0	938,0	1347,3	1277,5	1269,0
		MWCV			26,2%	23,0%	18,4%	28,9%	19,5%	18,6%	19,9%	15,8%
	Males	NR			2	4	6	2	8	6	4	8
		N			241,0	166,0	385,7	137,0	191,8	219,0	548,0	270,8
		MWCV			27,3%	26,3%	18,2%	35,5%	27,7%	20,3%	20,1%	19,7%
South East	Females	NR	38	80	56	48	44	66	74	82	52	36
		N	10,4	13,8	25,5	16,2	9,0	11,5	27,0	22,8	21,0	27,7
		MWCV	30,7%	15,8%	17,9%	21,5%	20,4%	17,6%	16,5%	17,8%	17,7%	22,4%
	Males	NR	40	84	56	50	44	66	90	82	86	38
		N	39,1	54,0	51,9	36,1	23,7	45,3	49,7	70,4	55,7	44,3
		MWCV	20,3%	10,1%	12,6%	13,8%	15,9%	14,5%	10,9%	10,5%	13,2%	19,2%
South Minch	Females	NR	4	14	12	12	14	12	24	14	10	12
		N	28,5	48,7	48,0	53,2	135,0	86,8	29,5	37,6	63,6	30,5
		MWCV	54,6%	26,8%	40,5%	24,9%	57,0%	20,8%	36,7%	24,2%	36,7%	25,5%
	Males	NR	4	14	10	12	14	12	26	16	14	12
		N	47,5	35,7	57,0	83,5	40,6	74,2	35,2	22,3	47,3	39,0
		MWCV	44,4%	36,1%	43,6%	25,5%	54,9%	40,6%	28,8%	39,1%	26,2%	30,9%
Sule	Females	NR	4	6	6	28	6	34	18	4		20
		N	895,5	239,7	659,0	373,2	472,7	426,2	931,4	622,5		1203,0
		MWCV	24,5%	30,6%	22,7%	12,2%	23,9%	10,5%	14,1%	22,3%		11,3%
	Males	NR	6	6	6	28	4	34	18	4		20
		N	667,0	49,7	127,3	36,4	61,5	195,8	97,2	31,5		89,5
		MWCV	30,7%	49,2%	26,8%	24,7%	44,8%	12,4%	26,3%	46,2%		20,0%
Ullapool	Females	NR		2		2		4	4			6
		N		173,0		95,0		81,0	61,5			76,0
		MWCV		33,5%		43,4%		35,7%	46,0%			38,7%
	Males	NR		2		2		4	4			6
		N		21,0		57,0		12,0	32,0			113,3
		MWCV		65,8%		42,6%		63,9%	41,8%			32,9%

Table 10.31 Adjusted empirical MWCV estimates for crab for all areas except Shetland, using double the sample size per record compared to the number in the raw data. These results use the version of the GLMER which contains as random effect gender, statistical area, month, assessment area and year.

Glmer(AGYMI) Unweighted Crab LogitBias Corrected Doubled No. Sampled MWCV Summary												
Management Area	Gender	Variable	Year									
			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Clyde	Females	NR	3	3				1	3	1	3	1
		N	82,7	80,7				18,0	30,0	64,0	14,7	78,0
		MWCV	42,6%	46,8%				93,8%	52,4%	50,3%	54,1%	50,8%
	Males	NR	3	3				1	2	1	3	1
		N	218,7	96,0				52,0	72,0	180,0	72,0	248,0
		MWCV	38,2%	37,6%				66,1%	47,6%	50,0%	54,4%	49,9%
East Coast	Females	NR	14	10	25	26	25	35	25	33	30	21
		N	100,3	63,4	187,8	131,0	66,3	163,8	178,5	152,8	144,3	196,4
		MWCV	32,8%	30,2%	24,2%	17,0%	21,5%	18,2%	16,4%	12,8%	22,4%	14,0%
	Males	NR	15	10	25	27	26	35	25	35	32	22
		N	137,2	164,4	83,3	91,4	99,5	190,6	148,7	139,3	147,3	147,5
		MWCV	31,5%	24,1%	27,9%	19,6%	15,9%	15,1%	15,8%	15,2%	15,6%	13,8%
Hebrides	Females	NR	10	10	12	8	10	19	30	20	22	26
		N	167,2	353,0	258,3	683,3	789,0	550,6	304,1	725,7	406,2	416,5
		MWCV	40,0%	24,1%	20,7%	20,1%	18,5%	14,3%	18,3%	14,9%	23,0%	15,3%
	Males	NR	10	10	11	8	10	19	30	21	24	26
		N	73,0	200,2	92,0	137,8	93,0	109,4	91,7	141,7	117,3	162,5
		MWCV	60,1%	24,8%	30,1%	28,1%	33,9%	23,3%	21,4%	19,9%	23,9%	18,2%
North Coast	Females	NR	1	2	2			3	3	1	2	11
		N	160,0	723,0	824,0			670,0	515,3	1188,0	768,0	1507,1
		MWCV	44,1%	39,4%	30,8%			23,4%	26,3%	38,0%	36,7%	13,2%
	Males	NR	1	2	2			3	3	1	2	11
		N	40,0	121,0	76,0			167,3	424,0	868,0	637,0	154,7
		MWCV	65,4%	40,4%	56,3%			28,9%	29,0%	43,1%	38,9%	17,4%
Orkney	Females	NR	15	19	17	58	41	57	110	158	323	401
		N	152,7	174,3	133,2	92,8	138,2	127,0	226,0	76,0	119,0	200,7
		MWCV	26,9%	25,5%	23,2%	14,4%	18,8%	19,9%	11,3%	11,7%	6,9%	6,5%
	Males	NR	15	19	18	77	46	70	134	186	381	454
		N	111,9	119,3	147,8	146,0	134,1	181,7	187,6	162,4	146,4	145,7
		MWCV	21,3%	22,8%	17,6%	11,4%	12,5%	13,1%	9,2%	6,4%	5,0%	4,1%
Papa Bank	Females	NR		1	2	3	1	4	3	2	4	
		N		2158,0	3590,0	2258,0	1218,0	1876,0	2694,7	2555,0	2538,0	
		MWCV		36,1%	32,3%	25,9%	40,9%	27,3%	26,6%	28,5%	22,4%	
	Males	NR		1	2	3	1	4	3	2	4	
		N		482,0	332,0	771,3	274,0	383,5	438,0	1096,0	541,5	
		MWCV		34,0%	33,6%	24,7%	40,2%	30,1%	25,2%	28,1%	23,5%	
South East	Females	NR	19	40	28	24	22	33	37	41	26	18
		N	20,8	27,5	50,9	32,3	18,0	22,9	54,0	45,7	42,1	55,4
		MWCV	36,1%	19,3%	20,7%	25,0%	25,0%	22,2%	19,2%	20,4%	22,6%	27,1%
	Males	NR	20	42	28	25	22	33	45	41	43	19
		N	78,2	108,0	103,7	72,2	47,5	90,5	99,4	140,9	111,4	88,5
		MWCV	23,4%	11,2%	14,3%	15,3%	17,4%	15,8%	12,3%	12,1%	14,8%	20,6%
South Minch	Females	NR	2	7	6	6	7	6	12	7	5	6
		N	57,0	97,4	96,0	106,3	270,0	173,7	59,0	75,1	127,2	61,0
		MWCV	66,5%	30,3%	44,0%	28,1%	69,6%	23,7%	45,7%	27,4%	40,8%	28,1%
	Males	NR	2	7	5	6	7	6	13	8	7	6
		N	95,0	71,4	114,0	167,0	81,1	148,3	70,3	44,5	94,6	78,0
		MWCV	48,0%	42,6%	44,4%	29,1%	53,1%	44,4%	30,5%	42,2%	30,4%	34,0%
Sule	Females	NR	2	3	3	14	3	17	9	2		10
		N	1791,0	479,3	1318,0	746,4	945,3	852,5	1862,9	1245,0		2406,0
		MWCV	34,6%	36,1%	31,9%	15,5%	30,3%	13,9%	20,1%	31,0%		15,6%
	Males	NR	3	3	3	14	2	17	9	2		10
		N	1334,0	99,3	254,7	72,7	123,0	391,5	194,4	63,0		179,0
		MWCV	36,4%	48,7%	33,7%	26,4%	45,5%	15,5%	28,4%	45,8%		22,0%
Ullapool	Females	NR		1		1		2	2			3
		N		346,0		190,0		162,0	123,0			152,0
		MWCV		39,9%		51,0%		42,0%	50,2%			41,8%
	Males	NR		1		1		2	2			3
		N		42,0		114,0		24,0	64,0			226,7
		MWCV		65,0%		46,9%		66,0%	44,3%			37,6%

Table 10.32 Adjusted empirical MWCV estimates for scallops for all areas except the Irish Sea, using double the number of trips compared to the number in the raw data. These results use the version of the GLMER which contains as random effect statistical area, month, assessment area and year.

Glmer(AYMI) Weighted Scallop LogitBias Corrected Doubled Trip Count MWCV Summary										
Management Area	Variable	Year								
		2007	2008	2009	2010	2011	2012	2013	2014	2016
Clyde	NR	4	2			2	2	2	10	4
	N	117,5	168,0			123,0	96,0	146,0	124,8	262,0
	MWCV	30,5%	0,0%			36,8%	0,0%	42,7%	20,6%	31,5%
East Coast	NR	36	34	24	12	10	22	28	12	20
	N	226,2	232,7	252,9	211,2	245,2	195,2	202,7	238,2	214,7
	MWCV	12,5%	10,3%	14,0%	15,9%	19,2%	14,0%	14,9%	17,1%	17,7%
North East	NR	8	42	14	12	8	20	20	10	24
	N	232,5	207,0	221,4	225,2	184,3	212,0	169,4	230,0	249,8
	MWCV	18,9%	12,5%	16,5%	22,2%	21,4%	14,4%	17,1%	18,7%	21,4%
North West	NR	34	26	30	62	32	54	66	42	84
	N	240,7	223,0	237,4	163,9	144,1	210,3	178,8	179,9	168,0
	MWCV	11,8%	14,9%	12,3%	12,1%	14,5%	9,8%	8,8%	10,7%	12,2%
Orkney	NR	6	12	16	18	10	12	6	4	8
	N	188,0	177,8	136,1	138,0	168,2	122,8	170,7	226,5	189,8
	MWCV	27,0%	22,0%	17,8%	17,1%	19,4%	25,2%	32,1%	28,6%	21,4%
Shetland	NR	220	188	118	130	130	136	140	128	142
	N	106,2	106,0	100,6	99,8	94,4	99,3	99,0	100,1	97,8
	MWCV	5,0%	5,6%	6,3%	6,3%	6,2%	6,5%	6,9%	6,5%	6,0%
WoK	NR	48	60	60	42	30	66	72	98	86
	N	182,0	183,2	211,9	221,0	175,1	193,5	178,3	158,7	171,0
	MWCV	8,9%	8,1%	8,5%	9,1%	10,5%	8,3%	8,2%	10,7%	142,5

Table 10.33 Adjusted empirical MWCV estimates for scallops for all areas except the Irish Sea, using double the sample size per record compared to the number in the raw data. These results use the version of the GLMER which contains as random effect statistical area, month, assessment area and year.

Glmer(AYMI) Weighted Scallop LogitBias Corrected Doubled No. Sampled MWCV Summary										
Management Area	Variable	Year								
		2007	2008	2009	2010	2011	2012	2013	2014	2016
Clyde	NR	2	1			1	1	1	5	2
	N	235,0	336,0			246,0	192,0	292,0	249,6	524,0
	MWCV	36,6%	0,0%			46,2%	0,0%	55,0%	25,5%	31,9%
East Coast	NR	18	17	12	6	5	11	14	6	10
	N	452,3	465,4	505,8	422,3	490,4	390,4	405,4	476,3	429,3
	MWCV	16,8%	14,1%	19,1%	20,1%	26,4%	19,0%	20,3%	22,6%	22,4%
North East	NR	4	21	7	6	4	10	10	5	12
	N	465,0	414,1	442,9	450,3	368,5	424,0	338,8	460,0	499,6
	MWCV	25,6%	16,8%	22,3%	31,0%	27,6%	19,1%	22,9%	25,6%	16,1%
North West	NR	17	13	15	31	16	27	33	21	42
	N	481,4	446,0	474,8	327,8	288,3	420,6	357,6	359,7	336,0
	MWCV	16,5%	20,6%	16,3%	16,0%	17,8%	12,8%	11,3%	13,5%	15,6%
Orkney	NR	3	6	8	9	5	6	3	2	4
	N	376,0	355,7	272,3	276,0	336,4	245,7	341,3	453,0	379,5
	MWCV	36,2%	28,3%	22,9%	22,2%	25,6%	32,4%	40,5%	39,6%	28,0%
Shetland	NR	110	94	59	65	65	68	70	64	71
	N	212,3	212,0	201,1	199,6	188,9	198,6	198,1	200,2	195,6
	MWCV	6,3%	7,1%	7,9%	7,9%	7,8%	8,1%	8,8%	8,1%	7,5%
WoK	NR	24	30	30	21	15	33	36	49	43
	N	363,9	366,3	423,8	442,1	350,3	387,0	356,7	317,4	342,0
	MWCV	11,4%	10,4%	11,0%	11,6%	13,1%	10,8%	10,8%	13,7%	10,3%

11 TECHNICAL APPENDIX 2

Simulations to assess potential bias in LCA based estimates of fishing mortalities for crab and lobster, Scottish inshore fisheries

Two different models with known underlying fishing mortalities were used to generate catch-at-length data. These catch-at-length data were then analysed using length cohort analysis (LCA), and the estimates of fishing mortality obtained with this approach were compared to the known true underlying fishing mortalities. The two different data generation models that were used are referred to here as “Simple” and “Dynamic”.

The approaches described below do not make provision for any variation in fishing mortality over lengths above the minimum legal size, although in practice this is part of the LCA analyses reported in Mesquita, *et al.* (2016). The Fbar estimates reported there are a selected summary of fishing mortality estimates. Here the assumption is that the true fishing mortality is Fbar for all length classes above the minimum legal size limit.

11.1 “Simple” Data Generation Model

The model “Simple” involves generating numbers-at-length over the lifetime of a cohort using the following equation:

$$N_{l+1} = N_l e^{-(M + F_{bar})\Delta t_l} e^{-(M + F_{bar})\Delta t_l} \quad (11.1)$$

Where;

N_l is the number of individuals surviving to length class l,

N_0 is set to an arbitrary value of 100,

t_l is the age corresponding to the lower bound for length class l, calculated from the inverse von Bertalanffy function,

Δt is the age difference between the lower length bounds for length classes l and l+1 (the age corresponding to length l, t_l is calculated from the inverse of the von Bertalanffy growth function),

Δl is the length difference between the lower length bounds for length classes l and l+1 – since the length class width used in all analyses is 5 mm this value is always 5 mm,

M is natural mortality,

F_{bar} is fishing mortality quoted as an estimate for the relevant stock and gender in Mesquita, *et al.* (2016).

$$t_l = t_0 - \frac{1}{\kappa} \ln \left\{ 1 - \frac{l}{l_\infty} \right\} \quad (11.2)$$

The age difference for length class l whose length range between length l and l + Δl is

$$\Delta t_l = t_{l+\Delta l} - t_l$$

Using the inverse of the von Bertalanffy equation, this equates to

$$\Delta t_l = \left[t_0 - \frac{1}{\kappa} \ln \left\{ 1 - \frac{(l + \Delta l)}{l_\infty} \right\} \right] - \left[t_0 - \frac{1}{\kappa} \ln \left\{ 1 - \frac{l}{l_\infty} \right\} \right] = \frac{1}{\kappa} \ln \left\{ \frac{l_\infty - l}{l_\infty - (l + \Delta l)} \right\} \quad (11.3)$$

From the Baranov catch equation, catch-at-length is calculated as:

$$C_l = N_l \left(\frac{F_{bar}}{F_{bar} + M} \right) (1 - e^{-(M + F_{bar})\Delta t_l}) \quad (11.4)$$

Use of catch-at-length values calculated in this way for LCA assumes that a plot of catch-at-length for all lengths at a particular snapshot in time is the same as a plot of catch-at-length for all lengths over the history of a cohort. For this to hold, the population must be at equilibrium. A further assumption which is implied by how the various equations are used is that recruitment is a continuous process which is not subject to pulses or fluctuations.

11.2 “Dynamic” Data Generation Model

The model “Dynamic” generates catch-at-length data from a dynamic age-structured population model. In this model,

- 1) The relationship between recruitment and spawning biomass is a Beverton-Holt stock-recruitment relationship, with a steepness parameter h of 0.999. In this model, smaller values of the steepness parameter of, for example, $h=0.90$, frequently lead to stock collapse at the reported fishing mortality estimates. To avoid these collapses a value of steepness of close to $h=1$ was used.
- 2) Recruitment occurs at the beginning of each of the 12 months of the year, to a degree that can be varied in the model. Catch-at-length proportions reflecting this are calculated by offsetting the catch-at-length that would be obtained where spawning and recruitment only taking place at the beginning of January by a further 1/12, 2/12 ... etc. of a year and summing up lengths for each age class, across the 12 months.
- 3) Age classes are from 0 to 20, where 20 is a plus group.
- 4) Weights-at-age are calculated from lengths-at-age using the reported length-weight relationships and the reported von Bertalanffy length-age relationships.
- 5) Age-at-maturity was selected to be 5 years, although a different selection is not expected to change the results shown here to any substantial extent.
- 6) Selectivity is equal across ages. Although this is unlikely to be the case, this assumption seems implicit in the use of an average fishing mortality over a range of length classes as the basic estimate of fishing mortality (see Mesquita, *et al.*, 2016), across that particular length range. Use of this simplifying assumption suggests that the results from the simulation exercise could be optimistic with respect to the bias and variance of fishing mortality estimates from LCA because of the larger number of parameters that have to be estimated. It is reasonable to expect that a bias of -20% for length independent fishing mortality estimates demonstrated by the simulation results presented here would translate to a similar % bias in the length dependent fishing mortality estimates, although this has not been confirmed by the methods and results presented here.
- 7) The Baranov catch equation was used.

A variant of the Dynamic model where recruitment takes place at the beginning of each year and length structure is assumed to arise via a time invariant but potentially age dependent normal distribution of length-at-age.

The base case “dynamic” model used here runs over 20 years. For the base case analysis, the model is at equilibrium over the entire 20 years, where this equilibrium is governed by the reported biological parameters and the fishing mortality estimates F_{bar} as is reported for each stock and gender in Mesquita, *et al.* (2016).

Minimum size: Note that neither of these data generation schemas address the existence of a minimum legal size. The assumption is that, provided the lengths used in LCA are larger than the minimum (which they would be in practice), failure to explicitly model a minimum legal size will not invalidate the results produced here.

11.3 LCA Estimation Model

The LCA calculations involve the determination of the terminal population numbers by multiplying the catch-at-length by a factor Z/F, and then performing a back-calculation procedure using a version of Pope's approximation modified for length.

Years relevant to a description of the LCA model are as follows:

- y_{\min} ; This is the first year of catch-at-length (CAL) data which contributes information to the average CAL information for purposes of LCA estimation.
- y_{\max} ; This is the last year of catch-at-length data which contributes information to the average CAL information for purposes of LCA estimation.

Length classes relevant to a description of the LCA model are as follows:

- L_{smallest} ; this is the length class encompassing the smallest individual sampled over the period y_{\min} to y_{\max} .
- I_{\min} ; this is the smallest length class of CAL data used in the LCA back calculation procedure, and which contributes a fishing mortality estimate to the average over length classes I_{\min} to I_{\max} to give the final fishing mortality estimate.
- I_{\max} ; this is the largest length class of CAL data used in the LCA back calculation procedure, and which contributes a fishing mortality estimate to the average over length classes I_{\min} to I_{\max} to give the final fishing mortality estimate
- I_{term} ; this length class, which is always larger than I_{\max} is the length class at which the LCA back calculation procedure is initiated
- I_{inf} ; this is the length class that encompasses the von Bertalanffy parameter value I_{∞}
- I_{end} ; this is the largest length class used in the LCA procedure, and is normally the upper limit of the summation to determine the CAL including and above the I_{term} length class.

For the terminal location, the following equation is applicable under equilibrium:

$$\sum_{l=l_{\text{term}}}^{l=l_{\text{end}}} C_{y,l} = N_{y,I_{\text{term}}} \frac{F}{F+M} \left(1 - e^{-(F+M) \sum_{l=l_{\text{term}}}^{l=l_{\text{end}}} \Delta t_l} \right) \text{ where } \sum_{l=l_{\text{term}}}^{l=l_{\text{end}}} \Delta t_l \rightarrow \infty \text{ as } l_{\text{end}} \rightarrow l_{\text{inf}} \quad (11.5)$$

This rearranges to give the following approximate population numbers at the terminal location $N_{y,I_{\text{term}}}$

$$N_{y,I_{\text{term}}} \approx \frac{F+M}{F} \sum_{l=l_{\text{term}}}^{l=l_{\text{end}}} C_{y,l} = Z/F \sum_{l=l_{\text{term}}}^{l=l_{\text{end}}} C_{y,l} \quad (11.6)$$

For the purpose of the calculations shown here

$$l_{\text{end}} = l_{\text{inf}} + 3 \times \sigma_{\text{LAA}}$$

for the species, gender and assessment area with the largest value of $l_{\text{inf}} + 3 \times \sigma_{\text{LAA}}$. This is a value of 270 mm (for Shetland male brown crab). Given that the value of Z/F is in any case

a guess, results are also presented where the following is used to calculate the population numbers at the terminal location.

$$N_{y,l_{term}} = C_{y,l_{term}} Z / F \quad (11.7)$$

Three terminal length locations were initially tested;

- 1) The value of l_{term} was taken to be the length class immediately after l_{max} , i.e. $l_{term} = l_{max+1}$.
- 2) The value of l_{term} was set at the length bin that is midway between l_{max} and l_{inf} i.e. $l_{term} = l_{mid} = (l_{max} + l_{inf})/2$.
- 3) A value of l_{term} at the length interval immediately preceding l_{inf} , i.e. l_{inf-1} .

However, based on superior performance evident from preliminary simulations studies, we only present results here for $l_{term} = l_{mid}$.

Back-calculations proceed using the following equation repeatedly for ever reducing lengths, up to l_{min} :

$$N_{y,l} = [N_{y,l+1} e^{M\Delta t_l/2} + C_{y,l}] e^{M\Delta t_l/2} \quad (11.8)$$

The fishing mortalities are then calculated using the following:

$$F_{y,l} = \ln \left(\frac{N_{y,l}}{N_{y,l+1}} \right) / \Delta t_l - M \quad (11.9)$$

Given a simulation procedure that runs over 20 years, $y_{min} = 18$ and $y_{max} = 20$.

The LCA assumptions that have been made here can be divided into those relevant to the model that was used to generate the catch-at-length data, and those relevant to the estimation model that was used to perform the LCA calculations:

11.4 Base Case and Variants

Base case catch-at-length data generation model settings:

- 1) Equilibrium conditions are assumed to apply, a standard LCA assumption denoted by **Fvar** = "N" in Table 11.3 and Table 11.4.
- 2) Fishing mortality is the value of **Fbar** reported in Mesquita, *et al.* (2016).
- 3) Growth parameters L_{inf} , K , and length weight relationship parameters a and b are as reported in Mesquita, *et al.* (2016).
- 4) Natural mortality M values are as reported in Mesquita, *et al.* (2016).
- 5) For "Dynamic" the standard deviation of length-at-age (σ_{LAA}) is 8 mm, and the normal distribution is truncated and renormalised as necessary.
- 6) For "Dynamic", spawning and recruitment takes place in equal amounts every month of the year, i.e. **Spawning** = "Y" in Table 11.3 and Table 11.4.

Base case LCA estimation model settings:

- 1) The length range used for F estimation purposes are as reported in Mesquita, *et al.* (2016). The final F value is an average of the F estimates for the relevant length groups (i.e. between \bar{l}_{min} and \bar{l}_{max}) for the last 3 years.
- 2) The natural mortality used for LCA estimation purposes is equal to the value used for data generation.
- 3) The growth and length to weight parameters used for LCA estimation purposes are equal to the values used for data generation.

- 4) The random error σ_{CAL} applied to the catch-at-length data are set to be negligibly small.
- 5) The population number at the terminal location is Z/F times the catch in the terminal location and the value of Z/F = **2** since the base F/Z ratio was set equal to **0.5**. For the results presented the terminal location is taken at l_{mid} , i.e. the length group that has the midpoint between l_{max} and l_{inf} as either its maximum value or falls within its 5 mm width range.
- 6) Years used for estimation in “Dynamic” version are assumed to be the last **3** years in the sequence simulated from year 1 to year 20.
- 7) There is no iterative tuning of the value of Z/F.

An alternative to the version of the data generation involves the case that equilibrium conditions are not in effect, but all other base case settings are applicable (**Option # 10**). This situation is simulated by allowing the resource to start off at equilibrium in year 1 at $F_{bar}/2$ and then for the fishing mortality to increase linearly up to a value of $F_{bar} * 1.2$ in year 20 (for the fishing mortality estimates F_{bar} reported in Mesquita, *et al.* (2016)).

Variants involving changes in the base settings in the data creation model are as follows:

- 1) For “Dynamic”, the **standard deviation of the length-at-age**, σ_{LAA} , was changed from 8 mm to either **5** mm or 10 mm (results only shown for 5 mm).
- 2) Spawning and recruitment takes place only at the beginning of the year i.e. **Spawning = ‘N’** in Table 11.3 and Table 11.4.
- 3) Catch-at-length data are available with a random error, σ_{CAL} , of roughly 10% applied to each length class and year.

Variants involving changes to the base case settings in the LCA estimation model are as follows:

- 1) The natural mortality, **M** used for LCA estimation purposes was set equal to $1.5 \times$ the value used for data generation.
- 2) The growth parameter **k** used for LCA estimation purposes was set equal to $1.5 \times$ the values used for data generation.
- 3) The F/Z ratio was changed to either **0.25; 0.75;** or **2** which equates to terminal Z/F values of **4; 1.33;** and **0.5**, respectively.

These model variant options were tested on the base case as well as the alternate version where equilibrium conditions were not maintained.

Only the variants involving the use of a different value of natural mortality, growth rate and terminal fishing mortalities are used for the “Simplified” data generation model options.

11.5 Iterations

The analysis carried out here used four different iterative schemes for the terminal fishing mortality values. These are abbreviated here as follows:

No Iter CI: The population numbers in the terminal location is Z/F times the catch in the terminal location and the base case value of Z/F = **2**. No iterative updating of the terminal fishing mortality is implemented.

Iter CI: The population numbers in the terminal location is Z/F times the catch in the terminal location and the base case value of Z/F = **2**. Iterative updating of the terminal fishing mortality is implemented as follows

$$F_{l(\text{terminal})}^{\text{iterate+}} = \frac{F_{l(\text{terminal-1})}^{\text{iterate}} + F_{l(\text{terminal-2})}^{\text{iterate}} + \dots + F_{l(\text{terminal-}n_{LCA,\text{asymptote}})}^{\text{iterate}}}{n_{LCA,\text{asymptote}}} \quad (11.10)$$

No Iter ΣCI: The population numbers in the terminal location is Z/F times the cumulative catch from the terminal location to the maximum size class in the Catch-At-Length (CAL) data, using Z/F = 2. No iterative updating of the terminal fishing mortality is implemented.

Iter ΣCI: The population numbers in the terminal location is Z/F times the cumulative catch from the terminal location to the maximum size class in the CAL data, using Z/F = 2. Iterative updating of the terminal fishing mortality is implemented as follows

$$F_{l(\text{terminal})}^{\text{iterate+}} = \frac{F_{l(\text{terminal-1})}^{\text{iterate}} + F_{l(\text{terminal-2})}^{\text{iterate}} + \dots + F_{l(\text{terminal-}n_{LCA,\text{asymptote}})}^{\text{iterate}}}{n_{LCA,\text{asymptote}}} \quad (11.11)$$

Where an iterative schema is implemented $n_{LCA,\text{asymptote}} = 3$. The use of this procedure is motivated by a view that fishing mortalities for the larger size are likely to be equal, as is the case for the data generation schemas used here.

Implementation of the iterative versions involved 6 iterations, i.e. $n_{LCA,\text{iters}} = 6$, for both Iter CI and Iter ΣCI, and for brown crab and lobster.

11.6 Results

- Table 11.1 summarises the biological parameters used for brown crab including the estimate of fishing mortality.
- Table 11.2 summarises the biological parameters and fishing mortalities for each of the lobster stocks relevant to this study, for males and females.
- Table 11.3 summarises the 18 data creation and LCA estimation options that were investigated in estimating potential bias in estimate of fishing mortality as obtained using the LCA method. This table is relevant to the so-called “**Dynamic**” data creation procedure.
- Table 11.4 summarises the six data creation and LCA estimation options that were investigated in estimating potential bias in estimate of fishing mortality as obtained using the LCA method, for the “**Simple**” data creation procedure.
- Table 11.5 shows the bias in estimates of fishing mortality for brown crab, for 18 variants associated with the Dynamic data creation procedure with and without iterative adjustment using either Equation 11.7 or 11.6 to calculate the terminal population numbers.
- Table 11.6 shows the bias in estimates of fishing mortality for European lobster, for 18 variants associated with the Dynamic data creation procedure with and without iterative adjustment using either Equation 11.7 or 11.6 to calculate the terminal population numbers.
- Table 11.7 shows the bias in estimates of fishing mortality for brown crab, for 6 variants associated with the Simple data creation procedure.
- Table 11.8 shows the bias in estimates of fishing mortality for lobster, for 6 variants associated with the Simple data creation procedure.

Figure 11.1 to Figure 11.4 compare the proportion bias in the estimates of fishing mortality produced using the iterative procedure to the former non-iterative approach in the “Dynamic”

data creation model, for brown crab and lobster using either Equation 11.7 or 11.6 to calculate the terminal population numbers where $I_{term} = I_{mid}$.

Figure 11.5 to Figure 11.8 compare the percentage bias in the estimates of the fishing mortality produced by the “simple” data creation model, for brown crab and lobster using either equation 12.7 or 12.6 to calculate the terminal population numbers where $I_{term} = I_{mid}$.

11.7 Conclusions

- 1) Overall the results suggest the potential for considerable bias in the estimation of fishing mortality using LCA, for LCA as modelled here, which may differ from the precise details used in practice.
- 2) The degree of bias is generally greater for the “Dynamic” data creation model than for the “Simple” data creation model. Thus the bias one needs to contend with in management depends on what one assumes is the applicable theory of how length structure arises in the fishery – the LCA theory of how length structure arises is that (a) it is due to a continuous and time invariant recruitment process with (b) no unexplained variance in length at age. (a) is invalid if there is seasonality in spawning, and (b) seems quite unlikely. This is clear in comparing the percent bias reported in Table 11.5 and Table 11.7 for brown crab, and Table 11.6 and Table 11.8 for lobster.
- 3) Figure 11.1 and Figure 11.2, for brown crab, and Figure 11.3 and Figure 11.4 for lobster, show that for the “Dynamic” data creation model, the largest contributor to potential bias is the failure of the equilibrium assumption made by LCA. These results also indicate that an iterative updating scheme for the terminal fishing mortality value can in a number of cases substantially reduce the degree of bias.
- 4) In general, comparing Figure 11.1 and Figure 11.2, for brown crab, and Figure 11.3 and Figure 11.4 for lobster, the problem of bias in the estimation of fishing mortality seems to be more of a concern for lobster.

Table 11.1 Biological parameters for brown crab as used in this section. This includes the estimate of fishing mortality F_{bar} reported by Mesquita, et al. (2016).

Species	Area	Gender	κ	Linf	a	b	M	F_{term}	F_{bar}	Length Interval ΔL
Brown Crab	Clyde	M	0,197	220	0,000059	3,2140	0,100	0,500	-	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	-	145 - 190 mm
	East Coast	M	0,197	220	0,000059	3,2140	0,100	0,500	0,63	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,45	145 - 190 mm
	Hebrides	M	0,197	220	0,000059	3,2140	0,100	0,500	0,36	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,48	145 - 190 mm
	Mallaig	M	0,197	220	0,000059	3,2140	0,100	0,500	-	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	-	145 - 190 mm
	North Coast	M	0,197	220	0,000059	3,2140	0,100	0,500	0,22	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,30	145 - 190 mm
	Orkney	M	0,197	220	0,000059	3,2140	0,100	0,500	0,64	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,41	145 - 190 mm
	Papa Bank	M	0,197	220	0,000059	3,2140	0,100	0,500	0,29	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,30	145 - 190 mm
	Shetland	M	0,188	246	0,000080	3,1660	0,242	0,406	0,77	150 - 200 mm
		F	0,224	227	0,000240	2,8950	0,256	0,174	0,49	150 - 200 mm
	South East	M	0,197	220	0,000059	3,2140	0,100	0,500	0,77	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,57	145 - 190 mm
	South Minch	M	0,197	220	0,000059	3,2140	0,100	0,500	0,48	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,47	145 - 190 mm
	Sule	M	0,197	220	0,000059	3,2140	0,100	0,500	0,39	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	0,42	145 - 190 mm
	Ullapool	M	0,197	220	0,000059	3,2140	0,100	0,500	-	145 - 190 mm
		F	0,172	220	0,000302	2,8534	0,100	0,500	-	145 - 190 mm

Table 11.2 Biological parameters for lobster as used in this section. This includes the estimate of fishing mortality F_{bar} reported by Mesquita, et al. (2016).

Species	Area	Gender	κ	Linf	a	b	M	F_{term}	F_{bar}	Length Interval ΔL
European Lobster	Clyde	M	0,110	173	0,000126	3,3600	0,100	0,500	0,84	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,45	95 - 130 mm
	East Coast	M	0,110	173	0,000126	3,3600	0,100	0,500	0,36	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,48	95 - 130 mm
	Hebrides	M	0,110	173	0,000126	3,3600	0,100	0,500	0,38	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,29	95 - 130 mm
	Mallaig	M	0,110	173	0,000126	3,3600	0,100	0,500	-	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	-	95 - 130 mm
	North Coast	M	0,110	173	0,000126	3,3600	0,100	0,500	-	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	-	95 - 130 mm
	Orkney	M	0,110	173	0,000126	3,3600	0,100	0,500	0,48	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,33	95 - 130 mm
	Papa Bank	M	0,110	173	0,000126	3,3600	0,100	0,500	0,35	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,19	95 - 130 mm
	Shetland	M	0,112	188	0,001700	2,7970	0,100	0,316	0,19	110 - 150 mm
		F	0,136	184	0,000400	3,1230	0,100	0,452	0,33	110 - 150 mm
	South East	M	0,110	173	0,000126	3,3600	0,100	0,500	0,76	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,73	95 - 130 mm
	South Minch	M	0,110	173	0,000126	3,3600	0,100	0,500	0,86	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	0,83	95 - 130 mm
	Sule	M	0,110	173	0,000126	3,3600	0,100	0,500	-	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	-	95 - 130 mm
	Ullapool	M	0,110	173	0,000126	3,3600	0,100	0,500	-	95 - 130 mm
		F	0,130	150	0,000919	2,9220	0,100	0,500	-	95 - 130 mm

Table 11.3 A table of the different options that were explored for data creation and LCA estimation, for the “Dynamic” data creation model. These variants are numbered 1 to 18 and are used to cross reference to the F estimation results in a later table. Refer to Table 11.1 and Table 11.2 for more details regarding the “Base” values used in the data creation and LCA models for the various options. Numbers in red highlight the essential change made for that option.

Dynamic Model															
Option#	Data Creation											LCA			
	Linf	K	t0	a	b	M	Fterm	σ_{LAA}	σ_{CAL}	Spawning	Fvar	Fbar	M	K	F/Z
1	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	N	Base	Base	Base	Base
2	Base	Base	0	Base	Base	Base	Base	8	1,00E-01	Y	N	Base	Base	Base	Base
3	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	N	Base	Base * 1,5	Base	Base
4	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	N	Base	Base	Base * 1,5	Base
5	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	N	Base	Base	Base	Base * 0,5
6	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	N	Base	Base	Base	Base * 1,5
7	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	N	Base	Base	Base	Base * 4
8	Base	Base	0	Base	Base	Base	Base	5	1,00E-06	Y	N	Base	Base	Base	Base
9	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	N	N	Base	Base	Base	Base
10	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	Y	Base	Base	Base	Base
11	Base	Base	0	Base	Base	Base	Base	8	1,00E-01	Y	Y	Base	Base	Base	Base
12	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	Y	Base	Base * 1,5	Base	Base
13	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	Y	Base	Base	Base * 1,5	Base
14	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	Y	Base	Base	Base	Base * 0,5
15	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	Y	Base	Base	Base	Base * 1,5
16	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	Y	Y	Base	Base	Base	Base * 4
17	Base	Base	0	Base	Base	Base	Base	5	1,00E-06	Y	Y	Base	Base	Base	Base
18	Base	Base	0	Base	Base	Base	Base	8	1,00E-06	N	Y	Base	Base	Base	Base

Table 11.4 A table of the different options that were explored as regards data creation and the LCA estimator, for the “Simple” data creation model. These variants are numbered 1 to 6 and used to cross reference to the F estimation results in a later table. Refer to Table 11.1 and Table 11.2 for more details regarding the “Base” values used in the data creation and LCA models for the various options.

Simplified Model													
Option #	Data Creation									LCA			
	Linf	K	t0	a	b	M	Fterm	Fbar	M	K	F/Z		
1	Base	Base	0	Base	Base	Base	Base	Base	Base	Base	Base	Base	Base
2	Base	Base	0	Base	Base	Base	Base	Base	Base	Base	Base	Base	Base * 0,5
3	Base	Base	0	Base	Base	Base	Base	Base	Base	Base	Base	Base	Base * 1,5
4	Base	Base	0	Base	Base	Base	Base	Base	Base	Base	Base	Base	Base * 4
5	Base	Base	0	Base	Base	Base	Base	Base	Base	Base * 1,5	Base	Base	Base
6	Base	Base	0	Base	Base	Base	Base	Base	Base	Base	Base * 1,5	Base	Base

Table 11.5 F % bias estimated for brown crab using the Dynamic data creation model pertaining to the 18 data creation and F estimation variants considered. No iter CI and Iter CI refers to the F % bias estimates with and without iteration where Equation 11.7 was used to calculate $N_{y,iterm}$. No Iter Σ CI and Iter Σ CI refers to the F % bias estimates with and without iteration where Equation 11.6 was used to calculate $N_{y,iterm}$. $n_{LCA,asymptote} = 3$, $n_{LCA,iter} = 6$, $l_{term} = l_{mid}$

Area	Sex	LCA Type	"Dynamic" Brown Crab																		
			F Estimate % Bias																		
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	
East Coast	M	No Iter CI	-11.3%	-11.6%	-18.5%	40.5%	-19.2%	-8.0%	-3.3%	-8.3%	-11.2%	-57.7%	-59.4%	-62.7%	-31.1%	-65.6%	-54.0%	-48.1%	-58.0%	-57.1%	
		Iter CI	-11.3%	-11.8%	-19.6%	41.3%	-11.3%	-11.3%	-8.0%	-11.2%	-64.2%	-67.1%	-71.4%	-38.9%	-64.5%	-64.1%	-63.9%	-64.7%	-63.5%		
	F	No Iter Σ CI	-19.2%	-19.6%	-26.7%	28.8%	-30.4%	-14.2%	-6.2%	-14.6%	-19.2%	-70.4%	-71.2%	-74.8%	-50.9%	-79.5%	-65.2%	-54.6%	-69.7%	-69.8%	
		Iter Σ CI	-13.2%	-13.5%	-21.8%	38.8%	-13.2%	-13.2%	-13.2%	-9.0%	-13.1%	-66.4%	-67.3%	-74.3%	-41.7%	-66.4%	-66.4%	-66.4%	-65.5%	-65.7%	
Habrides	M	No Iter CI	-8.6%	-10.3%	-18.2%	46.9%	-18.8%	-4.3%	2.0%	-6.5%	-8.6%	-51.7%	-52.0%	-58.4%	-20.2%	-61.2%	-47.1%	-39.9%	-52.0%	-51.1%	
		Iter CI	-10.4%	-12.1%	-21.9%	45.9%	-10.4%	-10.3%	-10.3%	-7.7%	-10.3%	-61.0%	-60.9%	-70.8%	-31.3%	-61.5%	-60.8%	-60.6%	-61.5%	-60.3%	
	F	No Iter Σ CI	-20.2%	-20.7%	-29.8%	29.7%	-34.3%	-13.5%	-2.6%	-16.1%	-20.2%	-67.3%	-68.2%	-72.9%	-44.7%	-77.7%	-61.1%	-48.3%	-66.6%	-66.7%	
		Iter Σ CI	-13.1%	-13.8%	-25.2%	42.3%	-13.1%	-13.1%	-13.1%	-9.2%	-13.1%	-64.0%	-65.0%	-75.0%	-35.0%	-64.0%	-64.0%	-64.0%	-62.9%	-63.3%	
	M	No Iter CI	-0.1%	0.7%	-10.7%	60.9%	-15.0%	6.5%	16.6%	0.5%	-0.1%	-41.9%	-41.0%	-49.5%	-4.8%	-55.0%	-35.5%	-24.9%	-42.5%	-41.5%	
		Iter CI	-6.8%	-7.4%	-20.8%	53.8%	-7.1%	-6.8%	-6.6%	-5.9%	-6.8%	-59.6%	-57.5%	-70.6%	-27.4%	-60.7%	-59.1%	-58.5%	-60.7%	-58.9%	
	F	No Iter Σ CI	-21.5%	-20.3%	-31.6%	28.4%	-40.8%	-11.4%	7.0%	-18.8%	-21.5%	-66.8%	-67.1%	-72.3%	-44.1%	-78.9%	-58.8%	-40.4%	-66.6%	-66.3%	
		Iter Σ CI	-11.7%	-10.4%	-26.7%	47.3%	-11.7%	-11.7%	-11.7%	-8.8%	-11.7%	-64.4%	-65.0%	-77.9%	-33.0%	-64.5%	-64.4%	-64.4%	-63.9%	-63.8%	
North Coast	M	No Iter CI	-9.7%	-9.1%	-18.8%	44.9%	-19.2%	-5.8%	0.0%	-7.3%	-9.7%	-53.2%	-52.2%	-59.6%	-22.9%	-62.3%	-49.0%	-42.2%	-53.5%	-52.7%	
		Iter CI	-10.8%	-9.6%	-21.7%	44.5%	-10.9%	-10.8%	-10.8%	-7.9%	-10.8%	-61.5%	-59.5%	-70.7%	-32.6%	-61.9%	-61.3%	-61.1%	-61.8%	-60.8%	
	F	No Iter Σ CI	-20.0%	-19.1%	-29.2%	33.1%	-13.8%	-3.9%	-15.6%	-19.9%	-67.7%	-66.9%	-73.1%	-45.5%	-77.7%	-61.8%	-49.8%	-66.9%	-67.1%		
		Iter Σ CI	-13.3%	-12.6%	-24.6%	41.3%	-13.3%	-13.3%	-13.3%	-9.2%	-13.3%	-64.2%	-63.3%	-74.7%	-36.0%	-64.2%	-64.2%	-64.2%	-63.1%	-63.5%	
	M	No Iter CI	20.4%	19.1%	5.9%	96.1%	-2.9%	31.3%	48.9%	19.8%	20.4%	-18.1%	-16.4%	-29.2%	34.9%	-38.2%	-7.9%	9.7%	-18.4%	-17.7%	
		Iter CI	-1.8%	-7.0%	-23.0%	69.2%	-3.0%	-1.4%	-0.8%	-2.8%	-1.9%	-53.0%	-48.2%	-68.4%	-11.8%	-55.6%	-52.1%	-50.7%	-53.6%	-52.6%	
	F	No Iter Σ CI	-21.1%	-22.1%	-33.2%	31.6%	-46.6%	-5.7%	26.4%	-19.7%	-21.1%	-60.6%	-60.0%	-67.5%	-33.0%	-76.3%	-49.4%	-20.5%	-60.7%	-60.2%	
		Iter Σ CI	-11.6%	-13.3%	-35.9%	56.7%	-11.6%	-11.6%	-11.6%	-9.6%	-11.6%	-63.2%	-62.1%	-83.5%	-22.5%	-63.5%	-63.1%	-63.0%	-63.3%	-62.6%	
Orkney	M	No Iter CI	1.0%	3.3%	-11.4%	64.6%	-14.6%	7.9%	18.5%	1.6%	1.0%	-38.8%	-41.9%	-47.8%	1.6%	-52.5%	-32.2%	-21.0%	-39.3%	-38.4%	
		Iter CI	-7.2%	-3.9%	-23.9%	56.1%	-7.5%	-7.1%	-6.9%	-6.2%	-7.2%	-57.6%	-59.2%	-70.8%	-22.0%	-58.9%	-57.2%	-56.6%	-58.3%	-57.1%	
	F	No Iter Σ CI	-21.4%	-20.4%	-33.1%	30.6%	-41.2%	-10.8%	8.4%	-18.6%	-21.3%	-64.0%	-65.6%	-70.7%	-38.4%	-76.9%	-55.6%	-36.4%	-63.6%	-63.5%	
		Iter Σ CI	-12.5%	-11.6%	-30.6%	49.1%	-12.5%	-12.5%	-12.5%	-9.4%	-12.5%	-62.8%	-64.2%	-78.9%	-27.7%	-62.9%	-62.8%	-62.8%	-62.1%	-62.2%	
	M	No Iter CI	-11.5%	-9.6%	-18.7%	40.2%	-19.3%	-8.3%	-3.7%	-8.5%	-11.4%	-58.0%	-57.3%	-63.0%	-31.7%	-65.9%	-54.3%	-48.6%	-58.3%	-57.4%	
		Iter CI	-11.4%	-9.5%	-19.6%	41.0%	-11.5%	-11.4%	-11.4%	-8.1%	-11.4%	-64.3%	-65.1%	-71.4%	-39.2%	-64.6%	-64.2%	-64.1%	-64.8%	-63.6%	
	F	No Iter Σ CI	-19.2%	-17.7%	-26.5%	28.8%	-30.1%	-14.2%	-6.5%	-14.5%	-19.1%	-70.5%	-69.9%	-74.8%	-51.0%	-79.4%	-65.3%	-54.9%	-69.7%	-69.9%	
		Iter Σ CI	-13.2%	-11.6%	-21.7%	38.6%	-13.2%	-13.2%	-13.2%	-9.0%	-13.1%	-66.4%	-65.8%	-74.2%	-41.9%	-66.4%	-66.4%	-66.4%	-65.5%	-65.7%	
Papa Bank	M	No Iter CI	-6.9%	-6.6%	-17.1%	50.2%	-18.2%	-2.1%	5.1%	-5.2%	-6.9%	-49.2%	-49.2%	-56.3%	-16.0%	-59.6%	-44.2%	-36.2%	-49.6%	-48.6%	
		Iter CI	-9.7%	-9.0%	-22.2%	48.1%	-9.7%	-9.6%	-9.6%	-7.4%	-9.6%	-60.3%	-62.2%	-70.8%	-29.4%	-60.9%	-60.1%	-59.8%	-60.9%	-59.6%	
	F	No Iter Σ CI	-20.6%	-20.5%	-30.7%	29.8%	-36.0%	-13.1%	-0.4%	-16.7%	-20.5%	-66.7%	-66.9%	-72.5%	-43.5%	-77.7%	-60.0%	-45.9%	-66.1%	-66.2%	
		Iter Σ CI	-12.9%	-12.8%	-26.2%	43.8%	-12.9%	-12.9%	-12.9%	-9.2%	-12.9%	-63.7%	-64.3%	-75.7%	-33.4%	-63.7%	-63.7%	-63.7%	-62.7%	-63.0%	
	M	No Iter CI	7.3%	9.6%	-4.8%	73.8%	-11.0%	15.6%	28.6%	7.3%	7.3%	-32.9%	-35.1%	-41.8%	10.3%	-48.7%	-25.1%	-11.8%	-33.4%	-32.5%	
		Iter CI	-4.8%	-0.6%	-21.7%	59.9%	-5.3%	-4.7%	-4.4%	-4.9%	-4.8%	-57.1%	-58.5%	-69.9%	-21.3%	-58.8%	-56.5%	-55.6%	-58.1%	-56.5%	
	F	No Iter Σ CI	-21.9%	-19.9%	-32.8%	29.1%	-44.0%	-9.5%	14.4%	-19.7%	-21.9%	-64.5%	-64.4%	-70.5%	-39.9%	-78.0%	-55.2%	-32.7%	-64.4%	-64.1%	
		Iter Σ CI	-12.5%	-12.3%	-30.6%	49.1%	-12.5%	-12.5%	-12.5%	-9.4%	-12.5%	-62.8%	-63.0%	-78.9%	-27.7%	-62.9%	-62.8%	-62.8%	-62.1%	-62.2%	
Shetland	M	No Iter CI	-26.6%	-27.3%	-41.1%	25.3%	-30.8%	-25.0%	-22.8%	-24.0%	-26.4%	-73.5%	-73.6%	-81.6%	-50.4%	-78.1%	-71.5%	-68.4%	-73.6%	-72.9%	
		Iter CI	-28.0%	-29.5%	-44.6%	24.5%	-28.0%	-28.0%	-27.9%	-24.9%	-27.8%	-81.8%	-82.7%	-92.0%	-59.6%	-82.4%	-81.6%	-81.3%	-81.8%	-81.1%	
	F	No Iter Σ CI	-31.8%	-31.4%	-45.4%	18.9%	-16.3%	-26.7%	-28.0%	-24.1%	-27.3%	-30.6%	-81.3%	-81.5%	-88.0%	-63.2%	-87.0%	-78.1%	-72.0%	-80.8%	-80.7%
		Iter Σ CI	-28.9%	-29.1%	-46.1%	23.5%	-28.9%	-28.9%	-28.9%	-25.4%	-28.7%	-79.9%	-80.1%	-93.5%	-55.3%	-80.1%	-79.9%	-79.8%	-78.9%	-79.1%	
	M	No Iter CI	-33.2%	-34.1%	-51.3%	20.9%	-43.8%	-28.4%	-21.2%	-31.7%	-33.3%	-69.7%	-70.5%	-79.6%	-41.7%	-77.5%	-65.6%	-58.4%	-70.2%	-69.3%	
		Iter CI	-41.3%	-43.1%	-67.2%	14.9%	-41.6%	-41.2%	-41.1%	-39.0%	-41.4%	-86.7%	-86.6%	-96.5%	-62.0%	-87.8%	-86.2%	-85.6%	-87.7%	-86.2%	
	F	No Iter Σ CI	-45.7%	-46.3%	-62.7%	1.7%	-58.9%	-38.9%	-26.7%	-42.2%	-45.8%	-82.7%	-83.1%	-89.3%	-64.6%	-89.3%	-78.1%	-67.2%	-82.4%	-82.3%	
		Iter Σ CI	-47.6%	-48.5%	-77.3%	8.1%	-47.6%	-47.5%	-47.5%	-42.4%	-47.7%	-94.3%	-94.0%	-99.7%	-70.8%	-95.1%	-94.0%	-93.6%	-93.6%	-93.9%	
South East	M	No Iter CI	-13.5%	-19.8%	36.1%	-19.5%	-11.1%	-7.7%	-9.6%	-13.4%	-61.3%	-61.0%	-65.7%	-37.3%	-68.0%	-58.3%	-53.6%	-61.4%	-60.8%		
		Iter CI	-12.9%	-12.9%	-19.7%	37.5%	-12.9%	-12.8%	-8.7%	-12.7%	-65.5%	-64.5%	-71.5%	-42.1%	-65.7%	-65.4%	-65.4%	-65.6%	-64.8%		
	F	No Iter Σ CI	-18.6%	-18.5%	-25.1%	28.6%	-27.1%	-15.0%	-9.4%	-13.3%	-18.5%	-71.1%	-70.9%	-75.1%	-52.3%	-79.1%	-66.7%	-58.3%	-70.2%	-70.5%	
		Iter Σ CI	-14.1%	-13.9%	-21.1%	35.9%	-14.1%	-14.1%	-9.3%	-13.9%	-61.6%	-68.8%	-73.6%	-44.2%	-67.1%	-67.1%	-66.1%	-66.4%	-66.4%		
	M	No Iter CI	-12.1%	-12.9%	-20.2%	40.2%	-19.7%	-9.0%	-4.5%	-8.8%	-12.0%	-56.5%	-59.9%	-62.6%	-29.3%	-64.7%	-53.4%	-47.8%	-57.1%	-56.3%	
		Iter CI	-12.1%	-13.3%	-21.3%	41.0%	-12.1%	-12.1%	-8.4%	-12.1%	-62.7%	-60.8%	-70.7%	-35.8%	-62.9%	-62.6%	-62.5%	-62.7%	-61.9%		
	F	No Iter Σ CI	-19.3%	-20.0%	-27.6%	29.5%	-30.0%	-14.6%	-7.1%	-14.4%	-19.3%	-68.5%	-67.8%	-73.6%	-47.2%	-77.6%	-63.4%	-53.5%	-67.5%	-67.9%	
		Iter Σ CI	-13.8%	-14.5%																	

Table 11.6 F % bias estimated for lobster using the Dynamic data creation model pertaining to the 18 data creation and F estimation variants considered. No iter CI and Iter CI refers to the F estimates with and without iteration where Equation 11.7 was used to calculate $N_{y,iterm}$. No Iter Σ CI and Iter Σ CI refers to the F estimates with and without iteration where Equation 11.6 was used to calculate $N_{y,iterm}$. $n_{LCA,asymptote} = 3$, $n_{LCA,itors} = 6$, $l_{term} = l_{mid}$

Area	Sex	LCA Type	"Dynamic" European Lobster																	
			F Estimate % Bias																	
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Clyde	M	No Iter CI	-16,2%	-15,8%	-22,4%	32,0%	-17,1%	-15,9%	-15,5%	-9,6%	-16,2%	-64,2%	-63,8%	-69,4%	-41,0%	-66,6%	-63,3%	-62,1%	-62,6%	-64,2%
		Iter CI	-15,9%	-15,6%	-22,3%	32,4%	-15,9%	-15,9%	-15,9%	-9,5%	-15,9%	-64,5%	-64,5%	-70,3%	-41,0%	-64,6%	-64,5%	-64,5%	-62,7%	-64,5%
		No Iter Σ CI	-16,6%	-16,2%	-22,9%	31,5%	-17,8%	-16,1%	-15,6%	-9,8%	-16,6%	-66,3%	-65,8%	-71,7%	-43,9%	-70,0%	-64,8%	-62,8%	-64,0%	-66,3%
		Iter Σ CI	-16,0%	-15,6%	-22,4%	32,3%	-16,0%	-16,0%	-16,0%	-9,5%	-16,0%	-64,9%	-64,3%	-70,8%	-41,4%	-64,9%	-64,9%	-64,9%	-62,7%	-64,9%
Clyde	F	No Iter CI	-22,0%	-19,7%	-32,0%	27,2%	-31,6%	-17,7%	-10,9%	-15,8%	-22,1%	-58,4%	-57,9%	-65,5%	-29,9%	-67,3%	-54,0%	-46,4%	-57,9%	-58,0%
		Iter CI	-20,9%	-18,4%	-32,8%	30,6%	-20,9%	-20,9%	-20,9%	-14,0%	-20,9%	-62,3%	-61,8%	-73,0%	-32,6%	-62,5%	-62,3%	-62,2%	-61,6%	-61,8%
		No Iter Σ CI	-29,2%	-27,6%	-39,1%	16,7%	-40,6%	-23,6%	-14,0%	-20,6%	-29,1%	-68,0%	-67,7%	-74,3%	-44,8%	-77,3%	-62,6%	-51,8%	-65,4%	-67,4%
		Iter Σ CI	-23,8%	-22,3%	-36,3%	26,7%	-23,8%	-23,8%	-23,8%	-15,3%	-23,7%	-65,6%	-65,5%	-77,2%	-36,9%	-65,6%	-65,6%	-65,6%	-62,3%	-65,0%
East Coast	M	No Iter CI	-10,6%	-7,7%	-23,5%	47,4%	-16,8%	-8,3%	-5,1%	-7,5%	-10,6%	-54,5%	-55,9%	-63,6%	-21,6%	-61,4%	-51,6%	-47,3%	-54,5%	-54,5%
		Iter CI	-11,8%	-9,7%	-26,5%	46,8%	-11,9%	-11,8%	-11,8%	-8,4%	-11,8%	-61,7%	-63,6%	-74,3%	-29,2%	-62,0%	-61,5%	-61,4%	-62,6%	-61,7%
		No Iter Σ CI	-16,5%	-14,3%	-29,8%	39,1%	-26,2%	-12,6%	-6,9%	-12,0%	-16,5%	-63,6%	-64,8%	-72,1%	-35,6%	-72,7%	-58,9%	-50,9%	-62,4%	-63,6%
		Iter Σ CI	-12,8%	-10,5%	-28,0%	45,6%	-12,8%	-12,8%	-12,8%	-8,5%	-12,8%	-61,6%	-63,0%	-75,1%	-28,9%	-61,6%	-61,6%	-60,1%	-61,6%	-61,6%
East Coast	F	No Iter CI	-22,9%	-23,1%	-32,7%	25,4%	-31,8%	-18,9%	-12,7%	-16,2%	-22,9%	-59,5%	-59,1%	-66,3%	-31,9%	-67,9%	-55,4%	-48,3%	-58,8%	-59,1%
		Iter CI	-21,5%	-21,5%	-32,7%	28,9%	-21,5%	-21,5%	-21,5%	-14,2%	-21,5%	-62,8%	-63,6%	-72,8%	-33,9%	-62,8%	-62,7%	-61,7%	-62,2%	-62,2%
		No Iter Σ CI	-29,2%	-29,3%	-38,8%	16,1%	-39,9%	-24,1%	-15,4%	-20,4%	-29,2%	-68,3%	-68,0%	-74,5%	-45,6%	-77,3%	-63,2%	-53,1%	-65,6%	-67,8%
		Iter Σ CI	-24,1%	-24,2%	-35,8%	25,5%	-24,1%	-24,1%	-24,1%	-15,4%	-24,1%	-65,8%	-65,8%	-76,7%	-37,9%	-65,8%	-65,8%	-65,8%	-62,5%	-65,2%
Hebrides	M	No Iter CI	-11,1%	-10,3%	-23,5%	46,1%	-16,8%	-9,0%	-6,1%	-7,8%	-11,1%	-55,4%	-55,7%	-64,2%	-23,4%	-62,0%	-52,7%	-48,7%	-55,3%	-55,4%
		Iter CI	-12,0%	-11,1%	-25,9%	45,8%	-12,0%	-12,0%	-12,0%	-8,3%	-12,0%	-61,7%	-61,0%	-73,8%	-30,0%	-62,0%	-61,6%	-61,5%	-62,3%	-61,7%
		No Iter Σ CI	-16,4%	-15,4%	-29,2%	38,7%	-25,2%	-12,8%	-7,7%	-11,6%	-16,4%	-63,9%	-63,9%	-72,2%	-36,3%	-72,7%	-59,5%	-52,0%	-62,6%	-63,9%
		Iter Σ CI	-12,9%	-11,9%	-27,2%	44,7%	-12,9%	-12,9%	-12,9%	-8,5%	-12,9%	-61,8%	-61,7%	-74,6%	-29,9%	-61,8%	-61,8%	-60,3%	-61,8%	-61,8%
Hebrides	F	No Iter CI	-14,3%	-14,9%	-27,4%	42,6%	-29,2%	-7,2%	4,5%	-11,2%	-14,4%	-48,8%	-48,7%	-58,2%	-12,8%	-61,5%	-42,2%	-30,2%	-49,9%	-48,6%
		Iter CI	-16,7%	-17,3%	-34,7%	43,0%	-16,7%	-16,6%	-16,6%	-12,8%	-16,8%	-59,8%	-62,3%	-75,1%	-23,3%	-60,3%	-59,6%	-59,4%	-62,5%	-59,5%
		No Iter Σ CI	-28,6%	-28,7%	-41,1%	20,9%	-45,5%	-19,5%	-2,7%	-22,0%	-28,5%	-64,3%	-64,1%	-72,0%	-37,5%	-76,4%	-56,8%	-40,1%	-62,7%	-63,8%
		Iter Σ CI	-22,3%	-22,4%	-41,6%	35,6%	-22,3%	-22,3%	-22,3%	-15,0%	-22,2%	-64,2%	-64,8%	-81,4%	-28,8%	-64,3%	-64,2%	-64,2%	-61,7%	-63,5%
Orkney	M	No Iter CI	-12,9%	-13,3%	-23,3%	41,2%	-16,6%	-11,6%	-9,8%	-8,6%	-12,9%	-58,9%	-60,8%	-66,5%	-30,1%	-64,0%	-56,8%	-53,9%	-58,3%	-58,9%
		Iter CI	-12,9%	-13,1%	-24,0%	41,6%	-12,9%	-12,9%	-12,9%	-8,4%	-12,9%	-62,2%	-63,5%	-72,1%	-33,3%	-62,3%	-62,2%	-62,1%	-61,6%	-62,2%
		No Iter Σ CI	-15,8%	-16,2%	-26,5%	37,2%	-21,6%	-13,6%	-10,6%	-10,5%	-15,8%	-64,9%	-66,4%	-72,3%	-39,1%	-72,1%	-61,5%	-56,1%	-63,3%	-64,9%
		Iter Σ CI	-13,5%	-14,0%	-24,7%	41,0%	-13,5%	-13,5%	-13,5%	-8,5%	-13,5%	-62,7%	-64,2%	-72,9%	-33,8%	-62,7%	-62,7%	-62,7%	-60,9%	-62,7%
Orkney	F	No Iter CI	-17,0%	-17,9%	-29,1%	37,3%	-30,2%	-10,8%	-0,8%	-13,0%	-17,1%	-52,1%	-51,7%	-60,7%	-18,6%	-63,5%	-46,2%	-35,6%	-52,7%	-51,8%
		Iter CI	-17,9%	-19,0%	-33,9%	39,1%	-17,9%	-17,8%	-17,8%	-13,0%	-17,9%	-60,5%	-60,2%	-74,3%	-26,2%	-60,8%	-60,4%	-60,2%	-62,0%	-60,1%
		No Iter Σ CI	-28,8%	-29,5%	-40,7%	19,4%	-44,2%	-20,9%	-6,5%	-21,7%	-28,8%	-65,6%	-65,2%	-72,9%	-40,0%	-76,8%	-58,8%	-44,0%	-63,7%	-65,1%
		Iter Σ CI	-22,6%	-23,1%	-39,7%	32,9%	-22,6%	-22,6%	-22,6%	-15,0%	-22,6%	-64,6%	-63,9%	-80,0%	-31,4%	-64,6%	-64,6%	-64,6%	-61,8%	-64,0%
Papay Bank	M	No Iter CI	-10,3%	-8,8%	-23,4%	48,1%	-16,8%	-7,8%	-4,5%	-7,3%	-10,3%	-54,0%	-53,5%	-63,3%	-20,7%	-61,1%	-51,0%	-46,5%	-54,0%	-54,0%
		Iter CI	-11,7%	-9,9%	-26,8%	47,4%	-11,8%	-11,7%	-11,7%	-8,4%	-11,7%	-61,7%	-63,0%	-74,5%	-28,8%	-62,0%	-61,5%	-61,3%	-62,8%	-61,7%
		No Iter Σ CI	-16,6%	-15,0%	-30,2%	39,2%	-26,7%	-12,5%	-6,5%	-12,1%	-16,6%	-63,4%	-62,7%	-72,0%	-35,2%	-72,7%	-58,6%	-50,3%	-62,2%	-63,4%
		Iter Σ CI	-12,8%	-11,2%	-28,4%	46,1%	-12,8%	-12,8%	-12,8%	-8,5%	-12,8%	-61,5%	-60,8%	-75,3%	-28,4%	-61,5%	-61,5%	-61,5%	-60,0%	-61,5%
Shetland	F	No Iter CI	-1,8%	1,3%	-18,7%	65,9%	-23,1%	8,9%	27,5%	-1,9%	-2,0%	-34,9%	-33,2%	-47,4%	11,9%	-52,7%	-25,1%	-6,9%	-37,8%	-34,9%
		Iter CI	-13,1%	-7,1%	-39,4%	57,1%	-13,5%	-13,0%	-12,8%	-14,1%	-13,5%	-57,8%	-58,4%	-77,8%	-13,2%	-59,2%	-57,3%	-56,7%	-65,9%	-57,9%
		No Iter Σ CI	-26,0%	-24,5%	-40,9%	28,0%	-48,1%	-13,0%	13,6%	-21,5%	-25,8%	-58,4%	-57,4%	-67,8%	-26,3%	-73,7%	-48,1%	-23,8%	-57,6%	-57,9%
		Iter Σ CI	-21,7%	-19,3%	-50,6%	46,1%	-21,7%	-21,7%	-21,7%	-15,6%	-21,4%	-62,9%	-63,2%	-86,3%	-18,2%	-63,1%	-62,8%	-62,7%	-61,5%	-62,0%
South East	M	No Iter CI	1,2%	0,7%	-17,6%	72,3%	-14,2%	7,9%	17,8%	0,9%	0,7%	-36,8%	-36,7%	-50,6%	10,5%	-50,5%	-30,3%	-19,7%	-38,9%	-37,2%
		Iter CI	-13,2%	-15,2%	-39,5%	57,3%	-13,9%	-13,0%	-12,7%	-17,1%	-14,0%	-63,5%	-68,8%	-81,2%	-22,7%	-65,4%	-62,7%	-61,7%	-74,8%	-63,8%
		No Iter Σ CI	-17,9%	-18,8%	-35,7%	43,1%	-37,9%	-7,7%	9,9%	-15,1%	-17,7%	-56,2%	-56,1%	-67,3%	-20,7%	-70,5%	-47,5%	-29,9%	-55,8%	-55,5%
		Iter Σ CI	-12,8%	-14,0%	-40,5%	58,2%	-12,9%	-12,8%	-12,8%	-9,5%	-12,4%	-57,5%	-58,6%	-80,2%	-11,6%	-57,6%	-57,4%	-57,4%	-56,1%	-62,0%
South Minch	F	No Iter CI	-9,0%	-7,4%	-22,1%	50,3%	-18,4%	-5,2%	0,2%	-6,7%	-9,0%	-51,0%	-51,4%	-60,2%	-16,2%	-60,0%	-46,9%	-40,6%	-51,1%	-50,6%
		Iter CI	-11,2%	-9,6%	-27,1%	49,0%	-11,2%	-11,2%	-11,1%	-8,3%	-11,3%	-60,4%	-61,1%	-73,6%	-26,4%	-60,9%	-60,2%	-59,9%	-60,9%	-60,1%
		No Iter Σ CI	-19,2%	-18,2%	-32,5%	35,3%	-32,8%	-13,0%	-3,4%	-14,9%	-19,2%	-64,2%	-65,1%	-72,2%	-37,0%	-74,8%	-58,2%	-46,8%	-63,2%	-63,7%
		Iter Σ CI	-13,9%	-12,9%	-30,7%	45,7%	-13,9%	-13,9%	-13,9%	-9,6%	-13,8%	-62,7%	-63,9%	-77,7%	-29,0%	-62,7%	-62,7%	-61,3%	-62,0%	-62,0%
South East	M	No Iter CI	-15,6%	-15,9%	-22,5%	33,6%	-16,8%	-15,1%	-14,6%	-9,4%	-15,6%	-63,5%	-63,3%	-69,1%	-39,5%	-66,3%	-62,5%	-61,0%	-62,1%	-63,5%
		Iter CI	-15,3%	-15,6%	-22,3%	34,0%	-15,3%	-15,3%	-15,3%	-9,2%	-15,3%	-64,1%	-64,7%	-70,5%	-39,7%	-64,1%	-64,1%	-62,4%	-64,1%	-64,1%
		No Iter Σ CI	-16,2%	-16,5%	-23,2%	32,8%	-17,8%	-15,6%	-14,8%	-9,7%	-16,2%	-66,1%	-65,9%	-71,8%	-43,2%	-70,4%	-64,4%	-61,8%	-63,9%	-66,1%
		Iter <math																		

Table 11.7 F estimation bias estimated for brown crab using the Simple data creation model pertaining to the six data creation and F estimation variants considered. Cterm refers to the F % bias estimates where Equation 11.7 was used to calculate $N_{y,term}$; ΣCI refers to the F % bias estimates where Equation 11.6 was used to calculate $N_{y,term}$. $n_{LCA,asymptote} = 3$, $n_{LCA,ters} = 6$, $l_{term} = l_{mid}$.

"Simplified" Brown Crab								
Area	Sex	LCA Type	F Estimate % Bias					
			1	2	3	4	5	6
East Coast	M	Cterm	-1,0%	-8,0%	1,7%	5,6%	-8,4%	2,0%
		ΣCI	-4,8%	-13,7%	-1,1%	4,3%	-12,3%	-9,5%
	F	Cterm	0,1%	-9,3%	3,9%	9,5%	-9,7%	5,8%
		ΣCI	-6,3%	-18,4%	-0,9%	7,2%	-16,2%	-10,6%
Hebrides	M	Cterm	5,0%	-9,6%	11,4%	21,0%	-5,7%	17,6%
		ΣCI	-9,2%	-27,7%	-0,1%	15,2%	-19,8%	-11,4%
	F	Cterm	-0,4%	-8,9%	3,1%	8,1%	-9,7%	4,4%
		ΣCI	-5,7%	-16,8%	-1,0%	6,2%	-15,2%	-10,2%
North Coast	M	Cterm	22,4%	-1,0%	33,3%	50,8%	7,7%	48,8%
		ΣCI	-7,8%	-34,3%	7,1%	35,8%	-21,0%	-3,4%
	F	Cterm	6,3%	-9,1%	13,0%	23,1%	-6,4%	19,9%
		ΣCI	-8,7%	-27,9%	0,8%	16,9%	-21,1%	-10,3%
Orkney	M	Cterm	-1,1%	-7,8%	1,6%	5,4%	-8,4%	1,7%
		ΣCI	-4,7%	-13,3%	-1,1%	4,2%	-12,1%	-9,3%
	F	Cterm	0,9%	-9,7%	5,4%	11,9%	-9,4%	8,2%
		ΣCI	-7,0%	-20,8%	-0,8%	8,9%	-17,5%	-10,9%
Papa Bank	M	Cterm	10,9%	-7,3%	19,1%	31,8%	-1,4%	28,9%
		ΣCI	-9,6%	-31,7%	2,0%	22,6%	-21,3%	-9,3%
	F	Cterm	6,3%	-9,1%	13,0%	23,1%	-6,4%	19,9%
		ΣCI	-8,7%	-27,9%	0,8%	16,9%	-21,1%	-10,3%
Shetland	M	Cterm	-0,3%	-2,8%	0,6%	1,8%	-15,5%	1,4%
		ΣCI	-1,5%	-5,0%	-0,2%	1,5%	-17,0%	-4,1%
	F	Cterm	0,9%	-8,5%	4,8%	10,3%	-21,1%	7,2%
		ΣCI	-3,7%	-15,3%	1,2%	8,7%	-25,9%	-6,5%
South East	M	Cterm	-1,3%	-6,0%	0,6%	3,1%	-7,6%	-0,2%
		ΣCI	-3,2%	-9,2%	-0,9%	2,5%	-9,6%	-7,4%
	F	Cterm	-1,1%	-7,6%	1,5%	5,1%	-9,3%	1,6%
		ΣCI	-4,4%	-12,6%	-1,0%	4,0%	-12,7%	-8,8%
South Minch	M	Cterm	0,6%	-9,8%	4,9%	11,2%	-8,3%	7,5%
		ΣCI	-7,2%	-20,7%	-1,1%	8,4%	-16,3%	-11,4%
	F	Cterm	-0,2%	-9,1%	3,4%	8,5%	-9,7%	4,8%
		ΣCI	-5,9%	-17,3%	-1,0%	6,5%	-15,5%	-10,3%
Sule	M	Cterm	3,5%	-10,0%	9,2%	17,8%	-6,8%	14,3%
		ΣCI	-8,8%	-25,9%	-0,6%	13,0%	-19,0%	-11,7%
	F	Cterm	0,7%	-9,7%	5,0%	11,2%	-9,5%	7,6%
		ΣCI	-6,8%	-20,2%	-0,8%	8,5%	-17,2%	-10,9%

Table 11.8 F estimation bias estimated for lobster using the Simple data creation model pertaining to the six data creation and F estimation variants considered. Cterm refers to the F % bias estimates in which Equation 11.7 was used to calculate $N_{y,term}$. Σ CI refers to the F % bias estimates in which Equation 11.6 was used to calculate $N_{y,term}$. $n_{LCA,asymptote} = 3$, $n_{LCA,ters} = 6$, $l_{term} = l_{mid}$.

"Simplified" European Lobster								
Area	Sex	LCA Type	F Estimate % Bias					
			1	2	3	4	5	6
Clyde	M	Cterm	-1,3%	-2,5%	-0,8%	-0,3%	-32,3%	0,1%
		Σ CI	-0,3%	-0,6%	-0,2%	-0,1%	-7,0%	-0,4%
	F	Cterm	-2,8%	-10,8%	0,6%	5,6%	-13,1%	4,4%
		Σ CI	-4,7%	-13,4%	-0,9%	5,0%	-15,0%	-0,8%
East Coast	M	Cterm	-0,1%	-5,1%	1,7%	4,1%	-13,1%	7,2%
		Σ CI	-3,0%	-10,0%	-0,4%	3,2%	-16,3%	-0,6%
	F	Cterm	-2,8%	-9,9%	0,3%	4,7%	-12,5%	3,5%
		Σ CI	-4,3%	-12,1%	-0,9%	4,2%	-14,1%	-1,0%
Hebrides	M	Cterm	-0,3%	-4,7%	1,3%	3,4%	-12,7%	6,1%
		Σ CI	-2,7%	-8,9%	-0,4%	2,7%	-15,5%	-0,7%
	F	Cterm	-1,0%	-15,2%	5,5%	15,9%	-14,8%	16,0%
		Σ CI	-7,0%	-22,8%	0,6%	13,3%	-20,7%	3,6%
Orkney	M	Cterm	-0,6%	-3,0%	0,3%	1,4%	-10,8%	2,7%
		Σ CI	-1,5%	-4,8%	-0,4%	1,1%	-12,0%	-0,8%
	F	Cterm	-2,0%	-14,3%	3,5%	12,0%	-14,8%	11,6%
		Σ CI	-6,5%	-20,1%	-0,1%	10,2%	-19,3%	1,7%
Papa Bank	M	Cterm	0,0%	-5,2%	1,9%	4,5%	-13,3%	7,8%
		Σ CI	-3,2%	-10,7%	-0,4%	3,5%	-16,8%	-0,5%
	F	Cterm	7,2%	-14,3%	17,7%	35,5%	-10,5%	38,2%
		Σ CI	-5,7%	-28,7%	6,5%	29,0%	-22,6%	15,4%
Shetland	M	Cterm	9,7%	-5,1%	15,9%	24,9%	-9,7%	35,7%
		Σ CI	-6,5%	-26,3%	3,0%	18,7%	-25,4%	6,0%
	F	Cterm	0,3%	-8,0%	3,6%	8,1%	-13,0%	11,9%
		Σ CI	-4,9%	-16,0%	-0,3%	6,4%	-18,5%	0,2%
South East	M	Cterm	-0,3%	-0,7%	-0,2%	0,0%	-7,0%	0,2%
		Σ CI	-0,4%	-0,9%	-0,2%	0,0%	-7,1%	-0,4%
	F	Cterm	-1,8%	-4,9%	-0,5%	1,2%	-8,6%	0,1%
		Σ CI	-2,0%	-5,4%	-0,7%	1,1%	-8,9%	-1,2%
South Minch	M	Cterm	-0,2%	-0,5%	-0,2%	-0,1%	-6,1%	0,0%
		Σ CI	-0,3%	-0,5%	-0,2%	-0,1%	-6,2%	-0,3%
	F	Cterm	-1,4%	-3,8%	-0,5%	0,7%	-7,5%	-0,3%
		Σ CI	-1,6%	-4,0%	-0,6%	0,6%	-7,7%	-1,1%

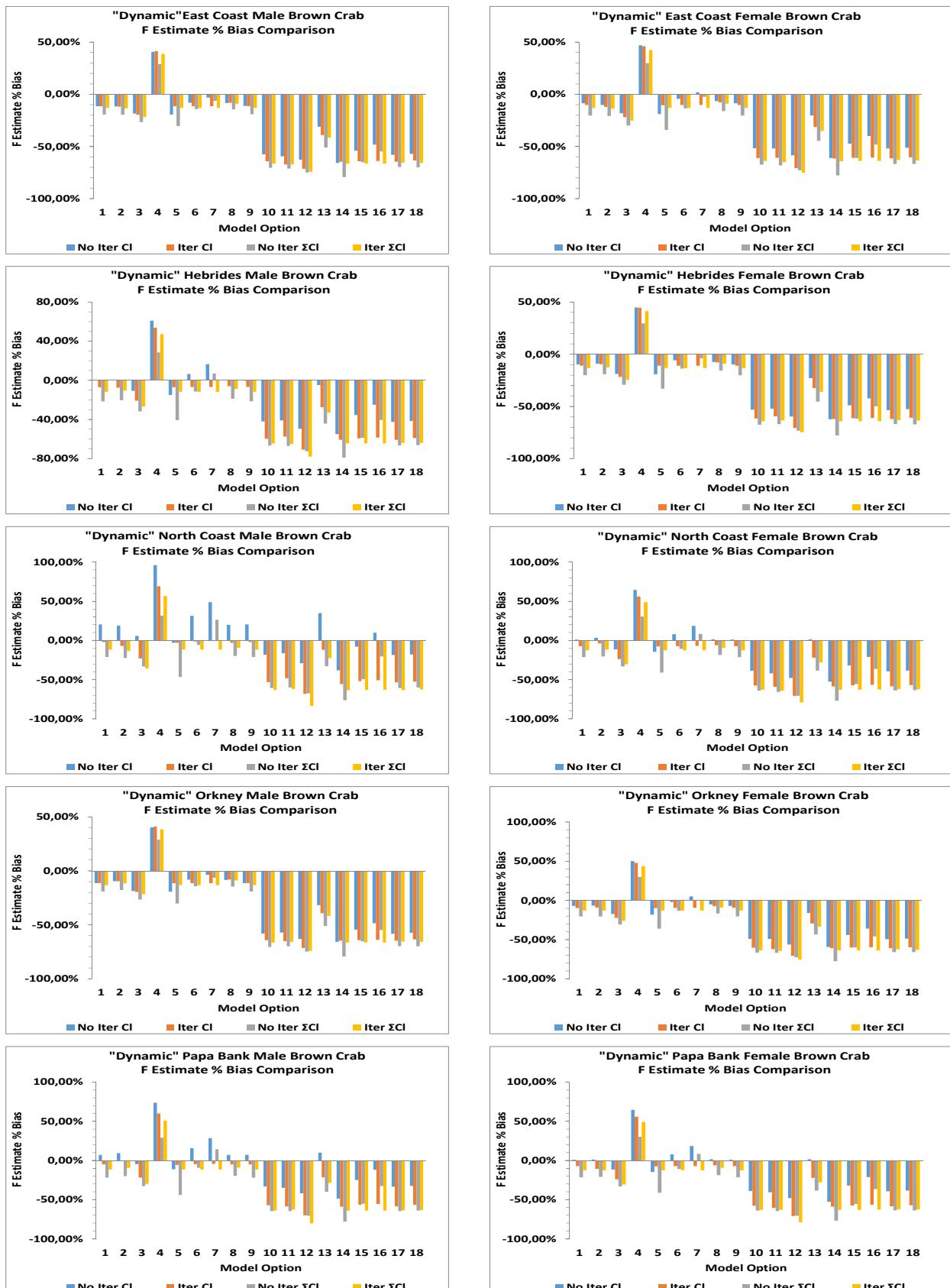


Figure 11.1 A comparison of the percentage bias in the estimation of fishing mortality from the "Dynamic" LCA model, for brown crab, for the cases where the terminal fishing mortality is set a priori (no iterations) No iter CI and No Iter Σ CI, or where it is iteratively improved on the assumption that selectivity is at an asymptote at large length classes (with iteration) Iter CI and Iter Σ CI.

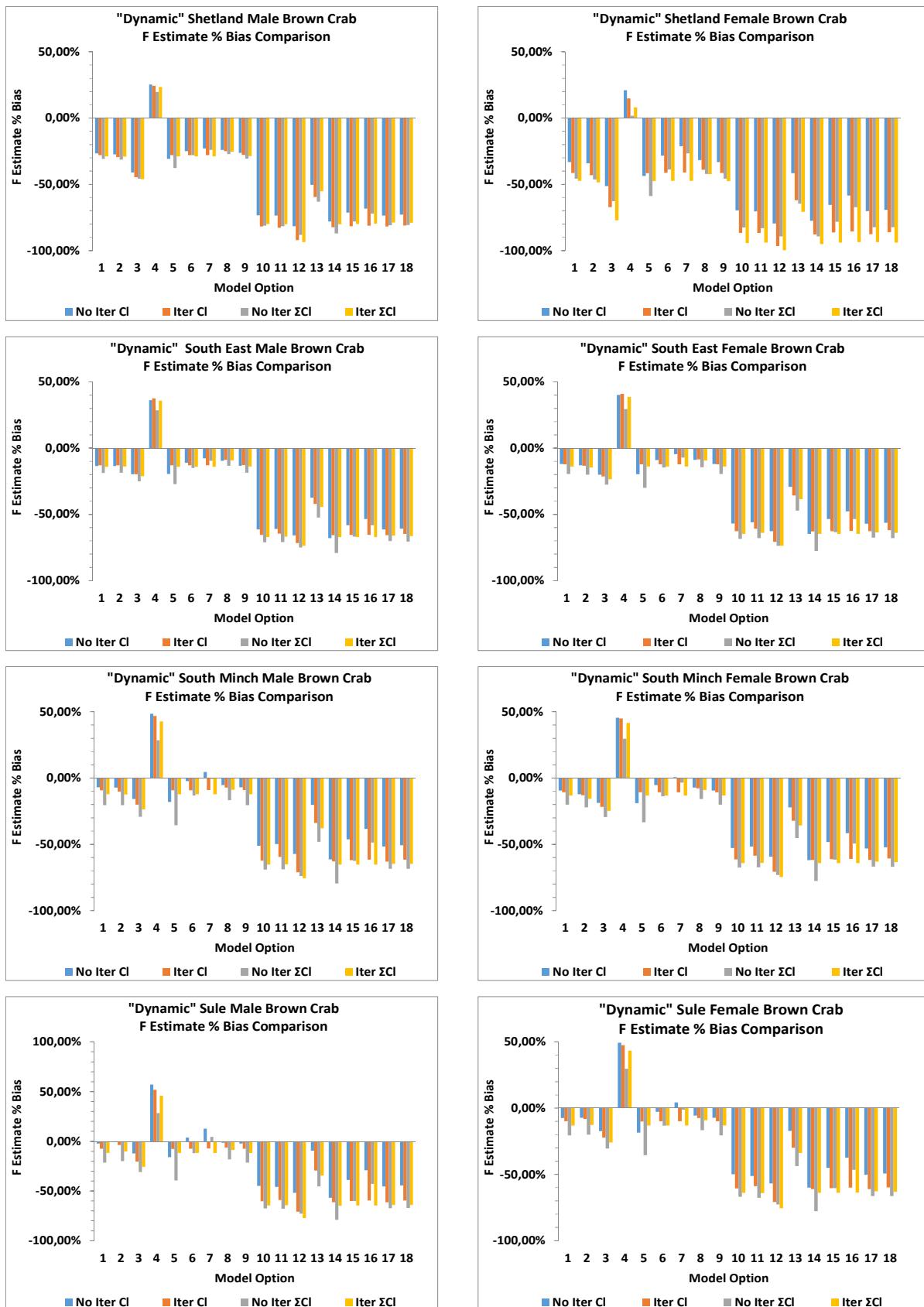


Figure 11.2 A comparison of the percentage bias in the estimation of fishing mortality from the "Dynamic" LCA model, for brown crab, for the cases where the terminal fishing mortality is set a priori (no iterations) No iter CI and No Iter Σ CI, or where it is iteratively improved on the assumption that selectivity is at an asymptote at large length classes (with iteration) Iter CI and Iter Σ CI.

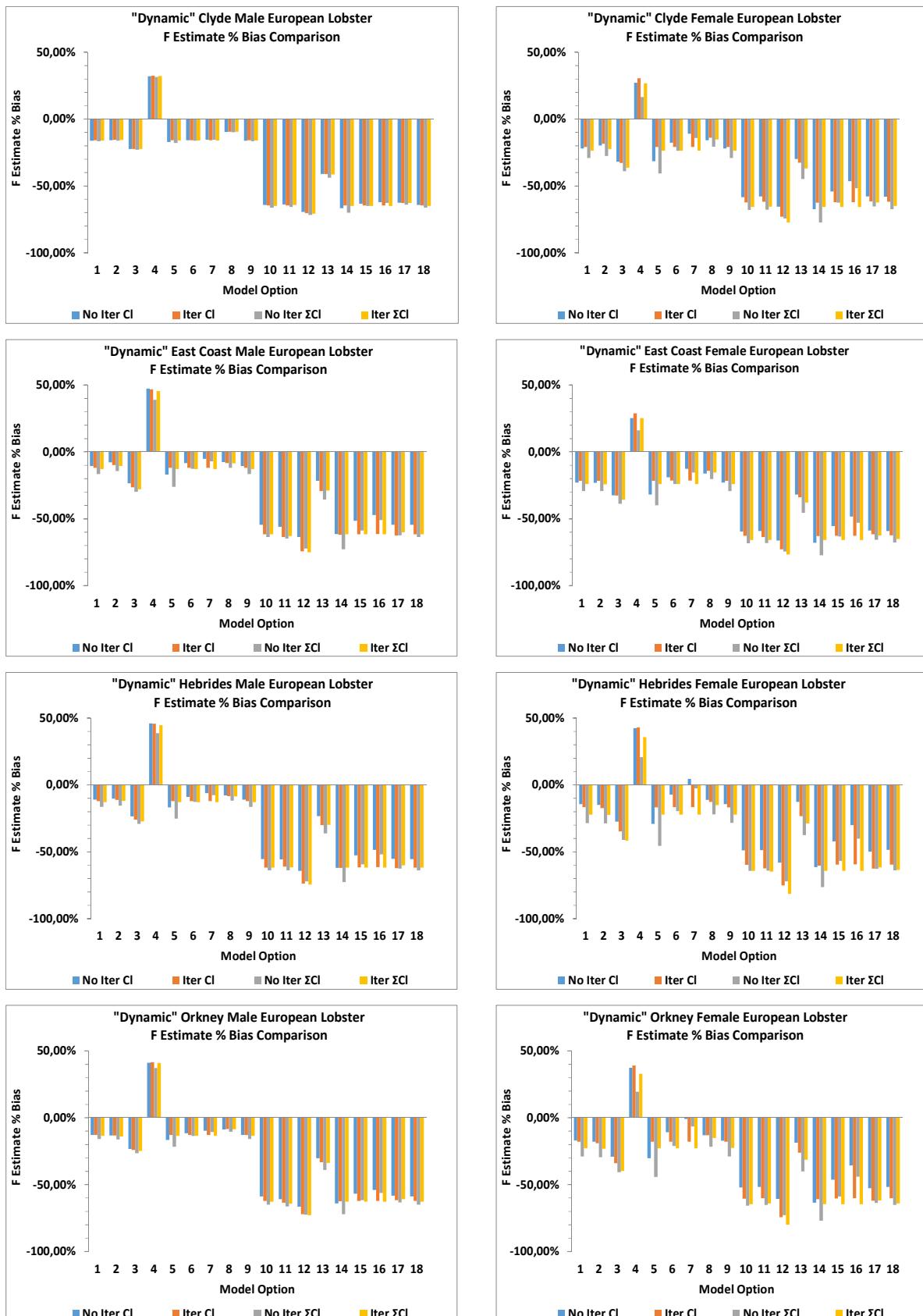


Figure 11.3 A comparison of the percentage bias in the estimation of fishing mortality from the “Dynamic” LCA model, for lobster, for the cases where the terminal fishing mortality is set a priori (no iterations) No iter CI and No iter Σ CI, or where it is iteratively improved on the assumption that selectivity is at an asymptote at large length classes (with iteration) Iter CI and Iter Σ CI.

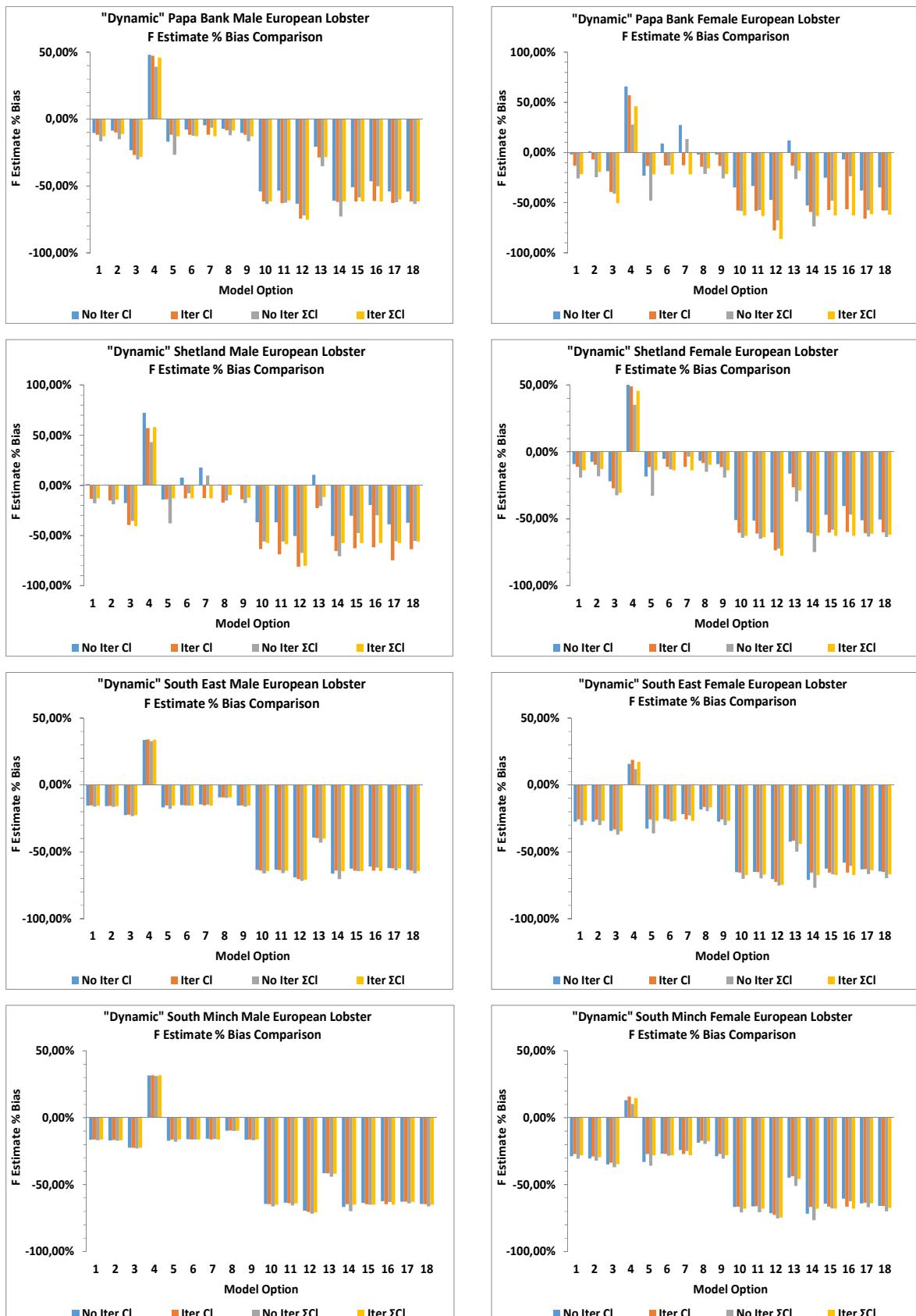


Figure 11.4 A comparison of the percentage bias in the estimation of fishing mortality from the “Dynamic” LCA model, for lobster, for the cases where the terminal fishing mortality is set a priori (no iterations) No iter CI and No Iter Σ CI, or where it is iteratively improved on the assumption that selectivity is at an asymptote at large length classes (with iteration) Iter CI and Iter Σ CI.

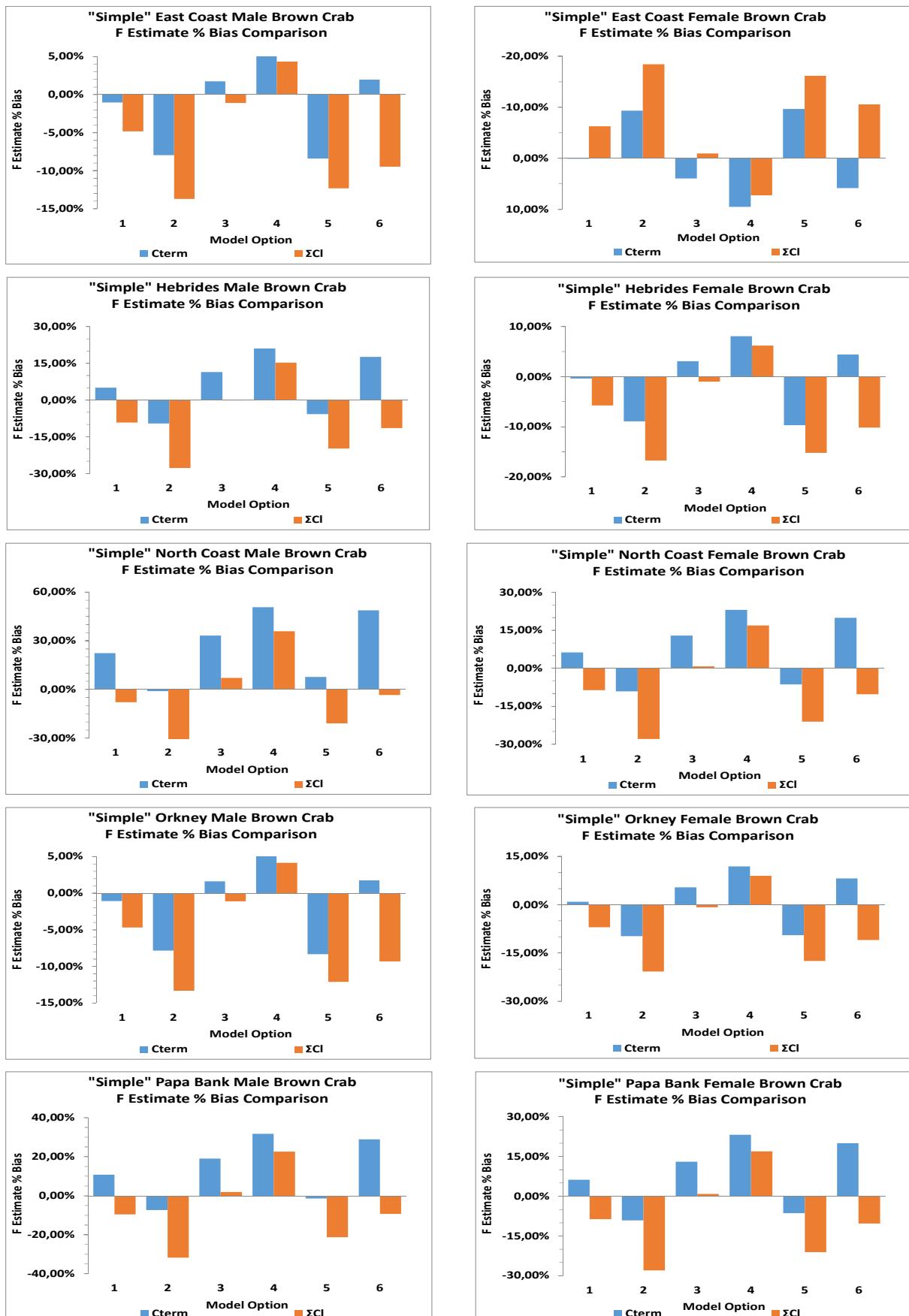


Figure 11.5 A comparison of the percentage bias in the estimation of fishing mortality from the “Simple” LCA model, for brown crab, for the cases Cterm and ΣCI where $N_{y,term}$ is calculated by Equation 11.7 and 11.6, respectively.

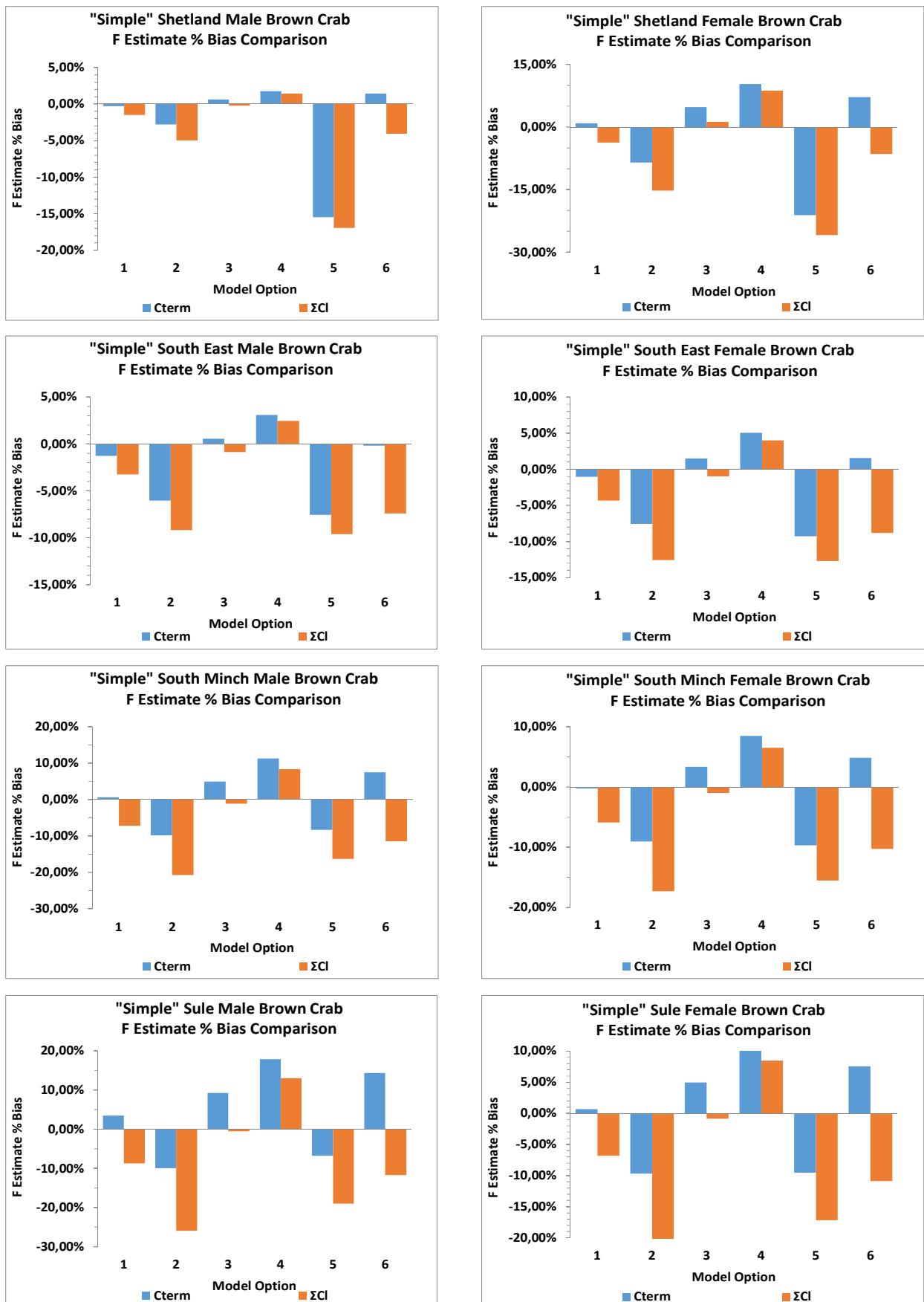


Figure 11.6 A comparison of the percentage bias in the estimation of fishing mortality from the "Simple" LCA model, for brown crab, for the cases Cterm and ΣCI where $N_{y,term}$ is calculated by Equation 11.7 and 11.6, respectively.

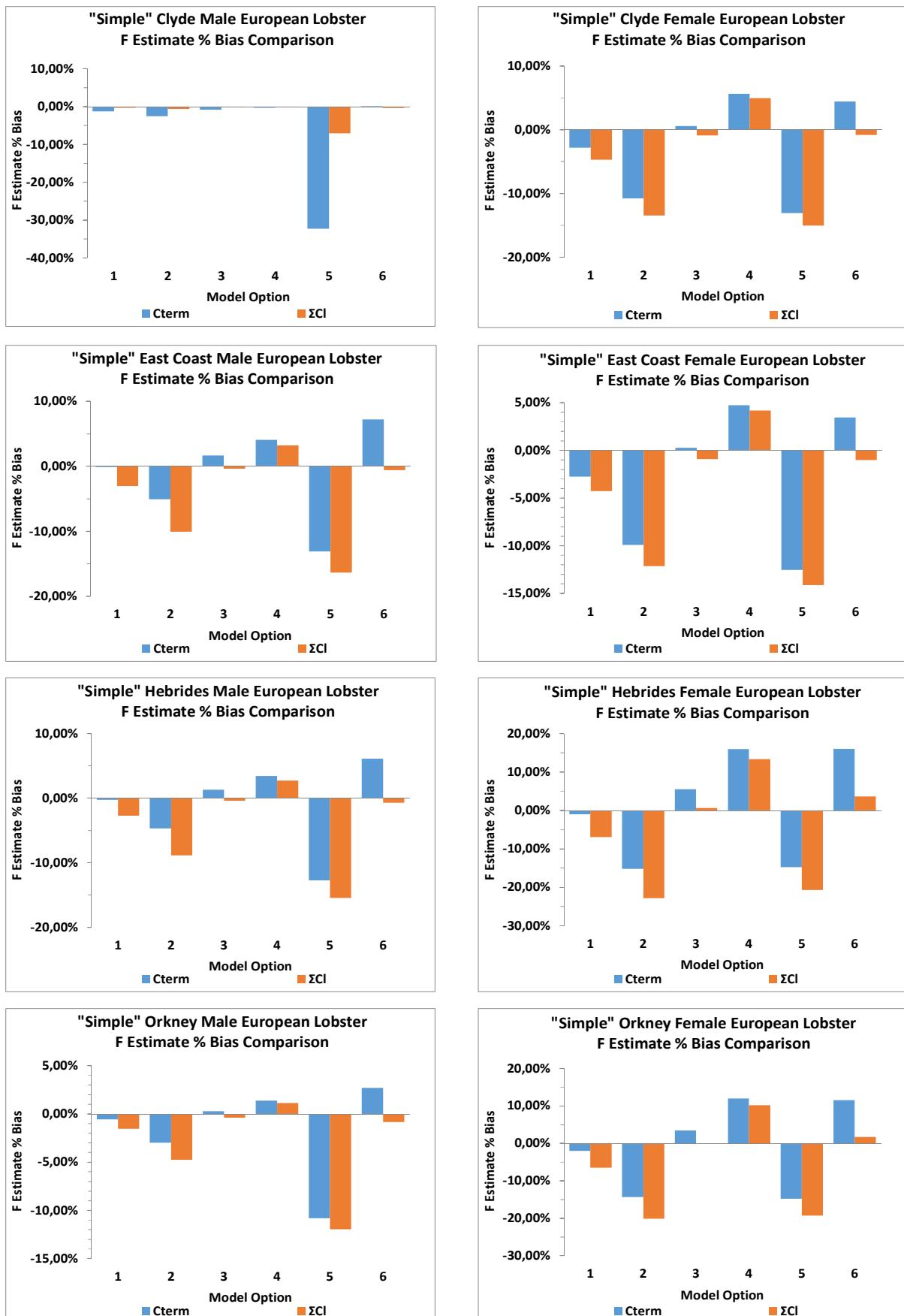


Figure 11.7 A comparison of the percentage bias in the estimation of fishing mortality from the "Simple" LCA model, for European lobster crab, for the cases Cterm and ΣCI where $N_{y,term}$ is calculated by Equation 11.7 and 11.6, respectively.

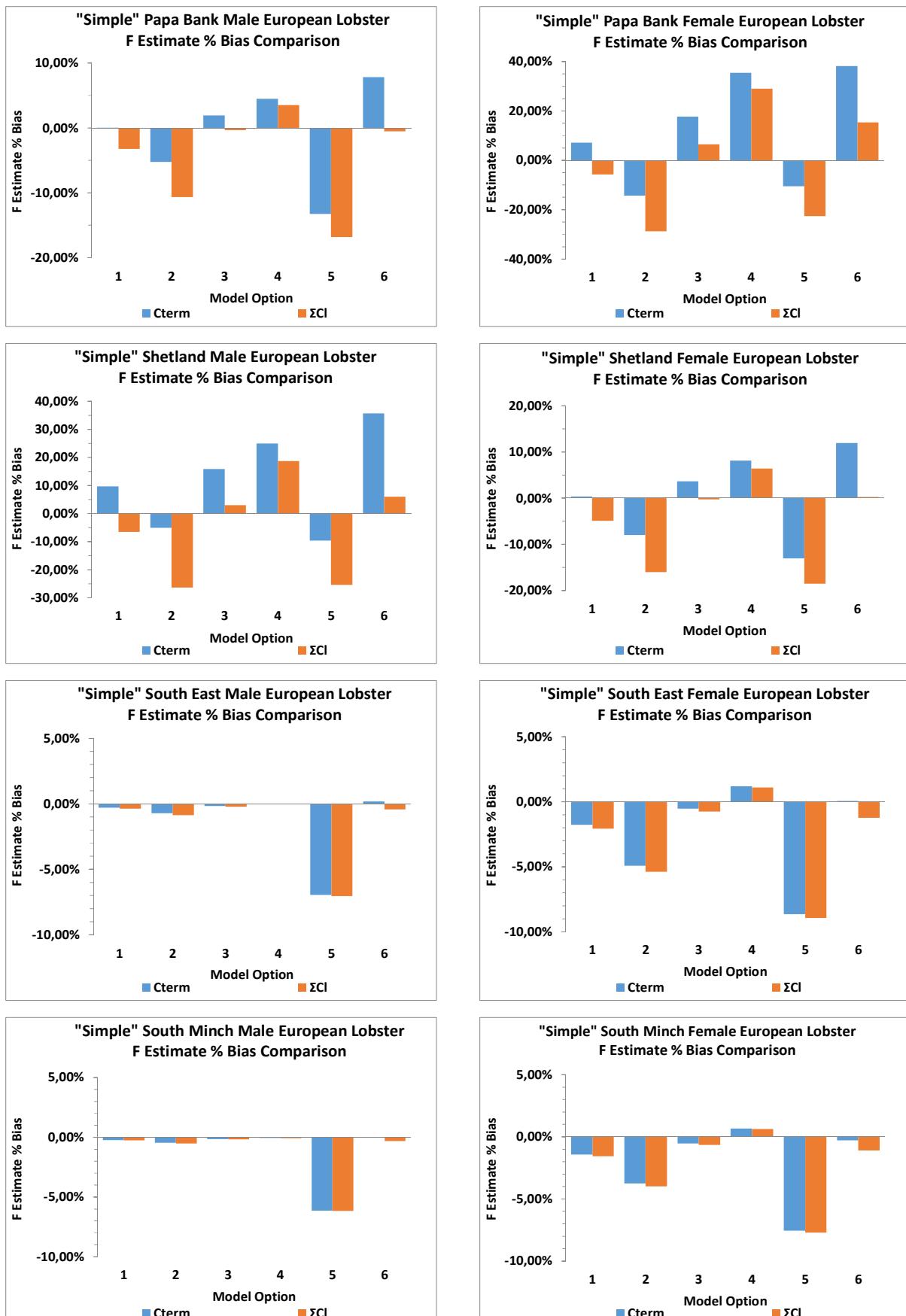


Figure 11.8 A comparison of the percentage bias in the estimation of fishing mortality from the "Simple" LCA model, for European lobster crab, for the cases Cterm and ΣCI where $N_{y,term}$ is calculated by Equation 11.7 and 11.6, respectively.

12 TECHNICAL APPENDIX 3

Simulations to assess likely variance in LCA based estimates of fishing mortalities for crab and lobster, Scottish inshore fisheries.

A relevant issue for a review of LCA is the degree of uncertainty in the estimates of fishing mortality derived using this technique. Although some of the options explored in Technical Appendix 2 do include measurement error in the catch-at-length data used for the LCA work, here we revisit this with a view to establishing some baseline concepts which may (a) provide insight into the uncertainty just mentioned, and (b) establish a minimum “quality” measure for length frequency data that can be used to assess the adequacy of existing sampling sizes and sampling designs.

We consider here that the quality of length frequency data can be quantified by the Mean Weighted Coefficient of Variation (MWCV). The MWCV is a proportion weighted sum of the CVs of catch proportion in each length class. So, if p_l is the proportion of crab/lobster sampling for length class l of the catch in a given year, and if CV_l is the coefficient of variation of that proportion, then

$$MWCV = \sum_{\forall l} p_l CV_l. \quad (12.1)$$

This is a useful concept (see also Bergh, *et al.* (2009)), since it provides

- 1) a single number which can be used as the “currency” when referring to the quality of length frequency data, and
- 2) it can be extended to cater for more complex sampling designs than simple random sampling (to follow elsewhere in this document).

In order to investigate the uncertainty in fishing mortality estimates derived from LCA due to measurement error in catch-at-length, we use typical base case catch-at-length data obtained using the “Dynamic” data creation model mentioned in Technical Appendix 2. The main information relevant to LCA are the “true” proportions p_l of individuals caught in each length class. We use the version of LCA which iteratively updates the terminal fishing mortality value as described in Technical Appendix 2. In order to generate data from these true proportions with an easily quantifiable degree of sampling (or measurement) error, i.e. with a particular value of MWCV, we assume that the sampling process can be represented as a simple random multinomial sampling process. Of course this is not the case in reality, since typical catch-at-length data contains far more variance than is given by the multinomial variance equations. However, for the purpose of the simulations referred to in this section, this larger amount of variance can be allowed for by decreasing the multinomial sample size N until a value of MWCV that matches the actual data are achieved. Note that Smith and MaGuire (1983) also use a multinomial distribution to describe the sampling error in length frequency data but they assume that the additional variance arises from variance in the parameters of the multinomial distribution rather than because the effective sample size is less than the actual sample size.

Here the order of this matching exercise is reversed, since we simply produce tables and results for a range of MWCV values (by altering the multinomial sample size), to be used as references following the completion of analyses to determine the MWCV of the actual data (see elsewhere in this report).

Note that for the multinomial process the variance of the proportion p_l , $Var(p_l)$ is

$$Var(p_l) = p_l(1 - p_l)/N \quad (12.2)$$

and so the standard error of the proportion p_l is given by, approximately (we are not distinguishing between the true and estimated proportions very clearly in this development):

$$SE(p_l) = \sqrt{p_l(1 - p_l)/N} \quad (12.3)$$

The CV_l in percentage terms is:

$$CV_l = \left[\frac{(\sqrt{p_l(1 - p_l)/N})}{\bar{p}_l} \right] * 100 \quad (12.4)$$

Therefore, for the multinomial distribution:

$$MWCV_{multinomial} = \sum_{\forall l} \bar{p}_l \overline{CV}_l = \sum_{\forall l} \left\{ \left[\frac{(\sqrt{p_l(1 - p_l)/N})}{\bar{p}_l} \right] * 100 \right\} \bar{p}_l = \sum_{\forall l} \left\{ (\sqrt{p_l(1 - p_l)/N}) * 100 \right\}. \quad (12.5)$$

\bar{p}_l and \overline{CV}_l are the mean catch-at-length proportion and mean coefficient of variance values across all realizations. The generated catch-at-length values $\mathbf{C}_{y,l}$ for the selected cases for length classes between l_{min} and l_{term} ($l_{term} = l_{mid}$) were obtained from the "dynamic" data creation model and used to simulate 50 realizations of the catch-at-length proportions, p_l . The calculation of MWCV at each multinomial N tested was repeated five times in order to obtain rough estimates of their variance and the quantities shown in the graphs are the averaged values over those five repetitions. (although the value of $MWCV_{multinomial}$ was always quite close to the value produced using instead the multinomial variance equations).

Thirty realizations of catch-at-length proportion, p_l , (for length classes l_{min} to l_{term}) were used to estimate the coefficient of variance of the terminal fishing mortality using an iterative LCA procedure. Terminal fishing mortality values were iterated, with $n_{LCA,iter} = 13$, and at each iterate the updating equation for the terminal fishing mortality was

$$F_{l_{term}}^i = \frac{F_{l_{term}-1}^{i-1} + F_{l_{term}-2}^{i-1} + \dots + F_{l_{term}-n_{LCA,asymptote}}^{i-1}}{n_{LCA,asymptote}} \quad (12.6)$$

with $n_{LCA,asymptote} = 6$ and $l_{term} = l_{mid}$

The CV for the fishing mortality estimates is calculated as the standard deviation of the k estimates from the k different realizations of sets of p_l , divided by the mean of all fishing mortality estimates across those k estimates. The reported CVs shown in the graphs are averaged values from five repetitions and standard deviation error bars were determined from those repetitions at each multinomial N. The use of different values of the multinomial N gives rise to contrast between CV's and MWCVs, making it possible to graph the relationship between the two. Example results are reported below. From this, one concludes, for example, from the bottom of the three panels shown that in order to achieve a CV of no more than 15% for the F estimate for Shetland Crab (Males), the catch-at-length sample should have an MWCV of less than ~25%.

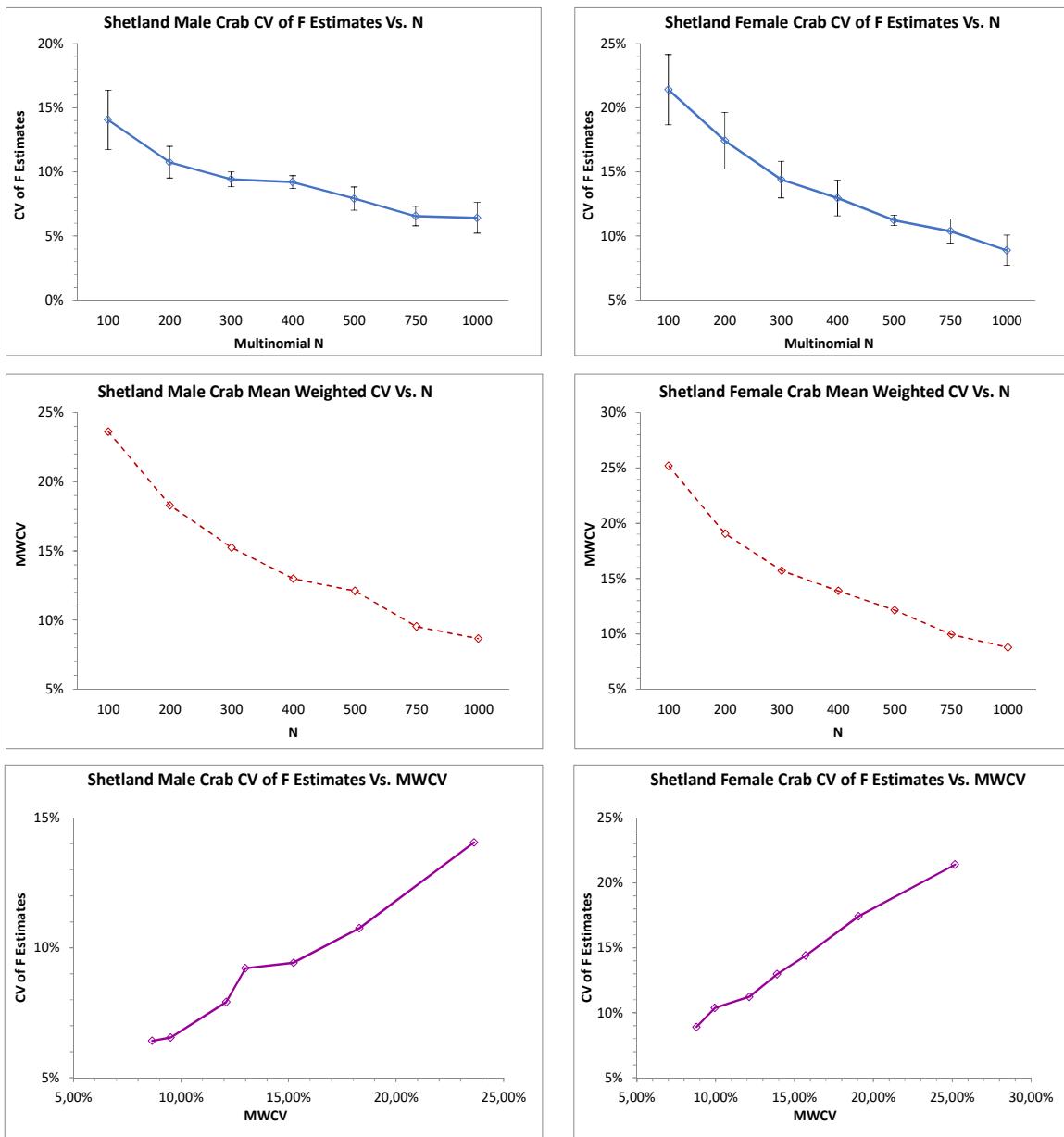


Figure 12.1 A) Top panel shows the relationship between the mean CV of the terminal fishing mortality and the value of the multinomial N for Shetland male and female brown crab (blue). B) Middle panels illustrate the relationship between the mean MWCV and the value of the multinomial N for Shetland male and female brown crab (dotted red). C) The Bottom panels demonstrate the relationship between the mean CV of the terminal fishing mortality estimate, and the mean MWCV of the length frequency data for Shetland male and female brown crab (purple).

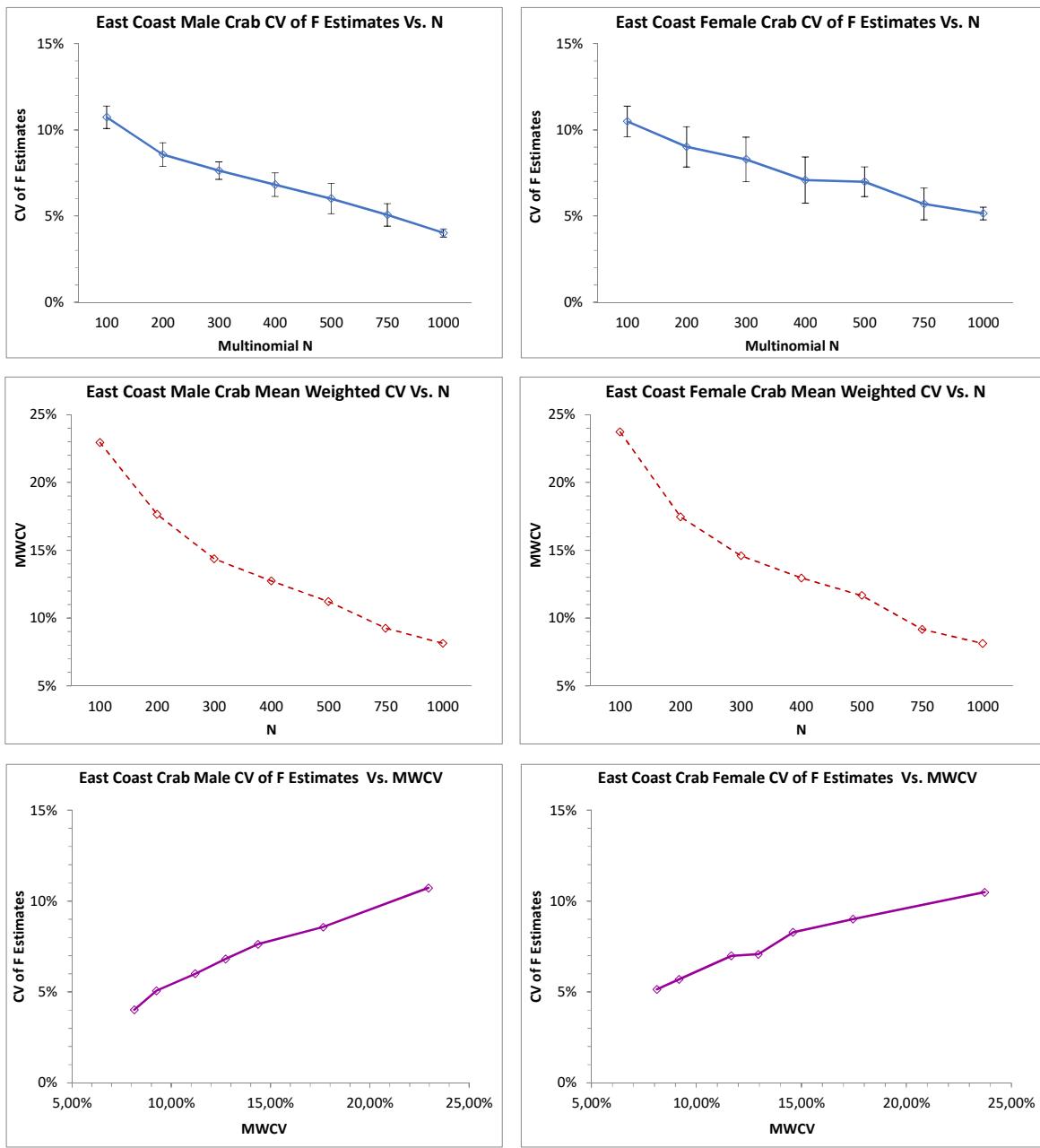


Figure 12.2. A) Top panels shows the relationship between the mean CV of the terminal fishing mortality and the value of the multinomial N for East Coast male and female brown crab (blue). B) Middle panels illustrate the relationship between the mean MWCV and the value of the multinomial N for East Coast male and female brown crab (dotted red). C) The Bottom panels demonstrate the relationship between the mean CV of the terminal fishing mortality estimate, and the mean MWCV of the length frequency data for East Coast male and female brown crab (purple).

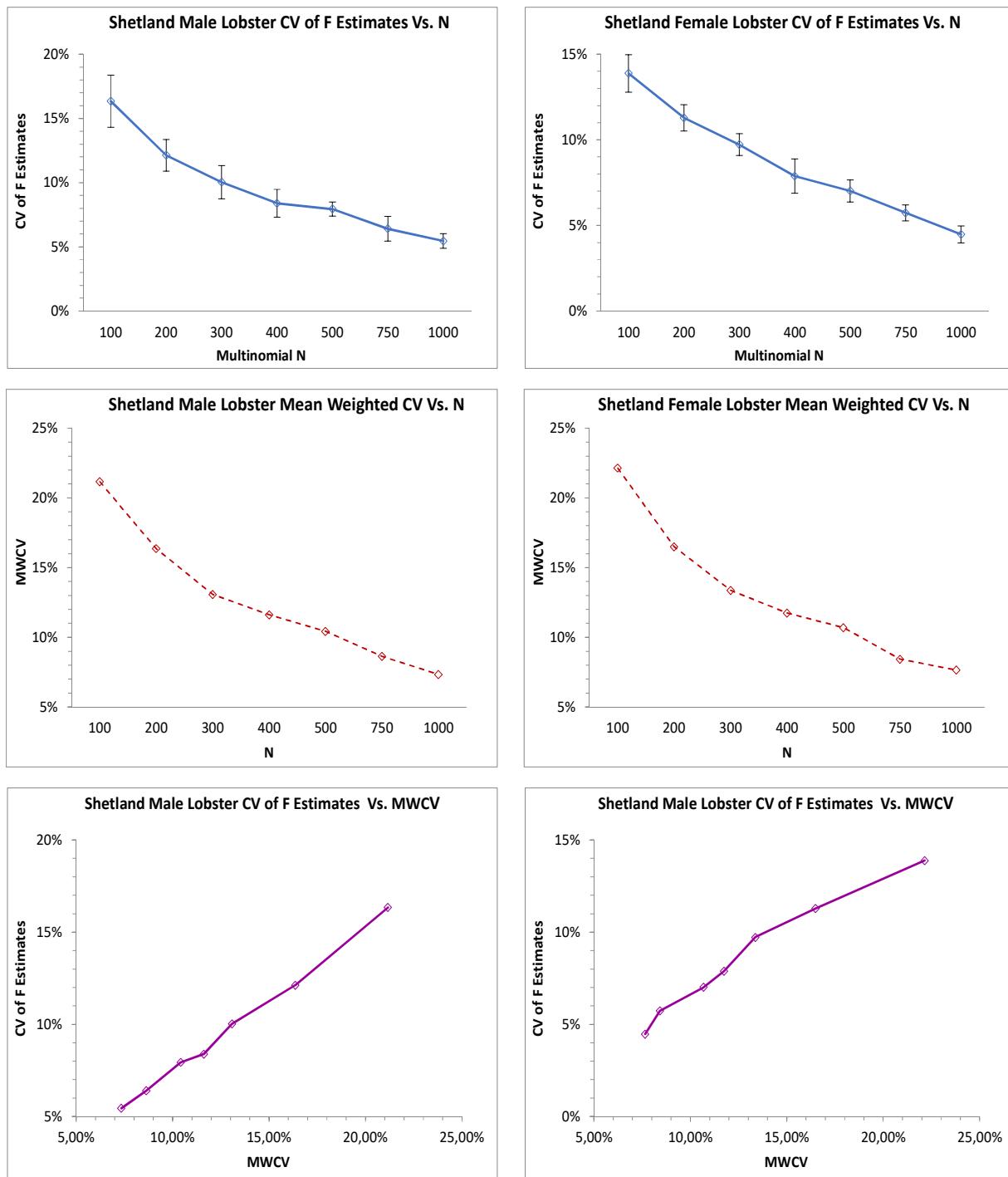


Figure 12.3 A) Top panels shows the relationship between the mean CV of the terminal fishing mortality and the value of the multinomial N for Shetland male and female lobster (blue). B) Middle panels illustrate the relationship between the mean MWCV and the value of the multinomial N for Shetland male and female lobster (dotted red). C) The Bottom panels demonstrate the relationship between the mean CV of the terminal fishing mortality estimate, and the mean MWCV of the length frequency data for Shetland male and female lobster (purple).

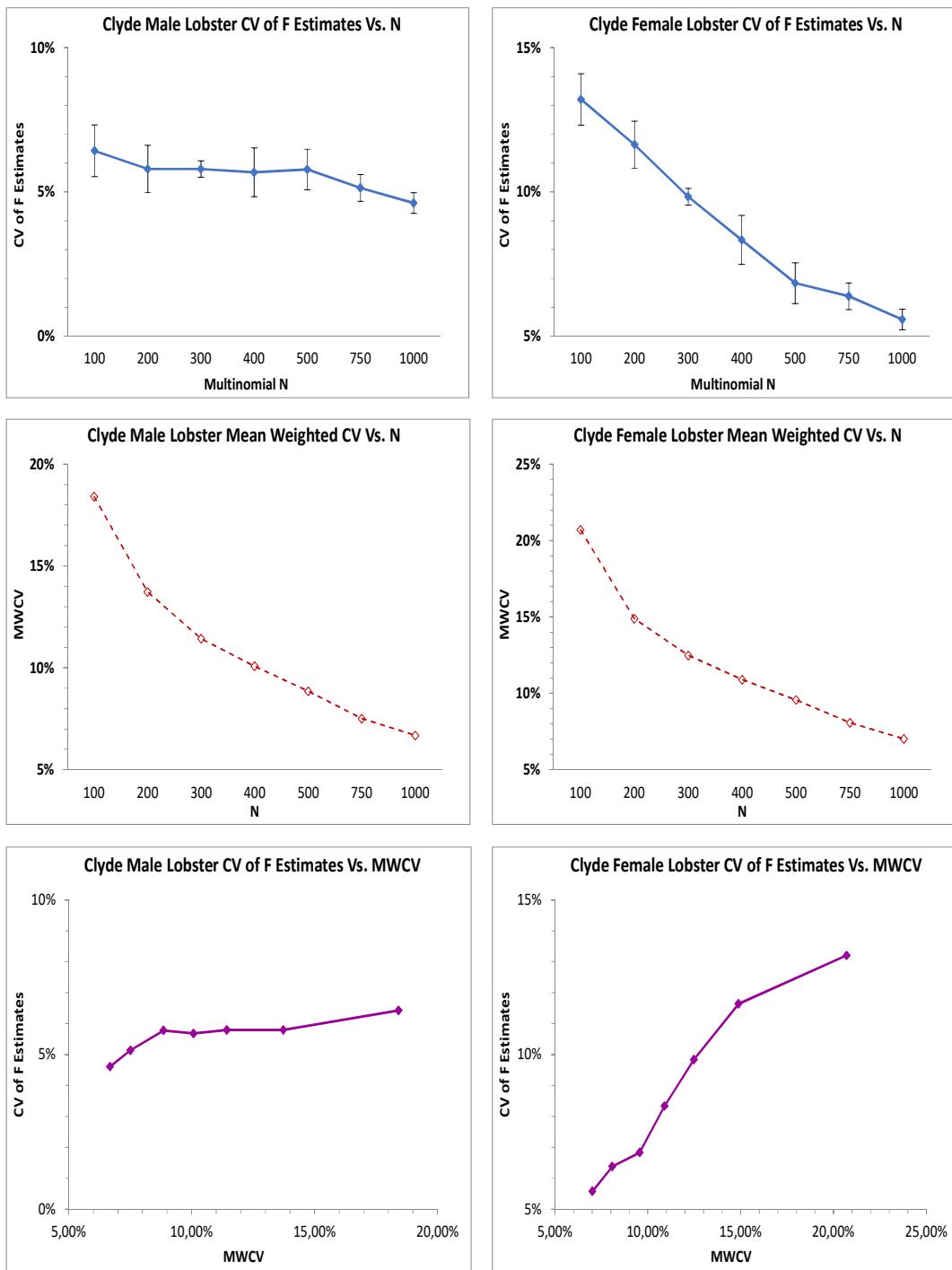


Figure 12.4 A) Top panels shows the relationship between the mean CV of the terminal fishing mortality and the value of the multinomial N for Clyde male and female lobster (blue). B) Middle panels illustrate the relationship between the mean MWCV and the value of the multinomial N for Clyde male and female brown crab (dotted red). C) The Bottom panels demonstrate the relationship between the mean CV of the terminal fishing mortality estimate, and the mean MWCV of the length frequency data for Clyde male and female brown crab (purple).

13 TECHNICAL APPENDIX 4

GLM results designed to assess whether daily catches could serve as a proxy for CPUE in Shetland crab and lobster fisheries.

The analyses carried out in this section are motivated in part by what seems to be potential for bias and estimation error (variance) in fishing mortality estimates produced by the Length Cohort Analysis (LCA) methodology (see Technical Appendix 2 and Technical Appendix 3). In particular, LCA cannot, by definition, determine whether there are trends in population size or in fishing mortality levels, because LCA is predicated on the equilibrium assumption. There is thus the possibility that, for example, negative trends in resource abundance are not being detected using LCA. This realization has implications for the return on investment achievable from novel approaches for gathering larger volumes of size structure information.

In the absence of biomass survey estimates, and in theory, catch-per-unit-effort provides a valuable additional index for input into resource management with the potential to provide insights on resource abundance trends. These have been used in a number of different ways:

- 1) In cases where VPA methods (which are closely related to LCA) are applied using catch-at-age data, it is common practice to tune the terminal fishing mortality estimates so that in the last year they conform to equal selectivity across the older age classes, while for the most recent occurrence of cohorts in the data - for the last age class plotted over time, the fishing mortalities are iteratively adjusted so that their trend over time matches the trend over time in fishing effort.
- 2) Alternatively, instead of the use of catch and effort data in a VPA analysis as described above, dynamic pool models, or simple replacement yield models can be run using only catch and effort data.

In practice of course at the present time, with the exception of Shetland, creel effort data are not widely available for creel fisheries for lobster and crab in Scottish inshore fisheries. In general terms, catch and effort data that are recorded for fisheries are limited to daily or weekly records of catches. In this type of situation a fishery must run the risk of being managed without the benefit of the resource abundance trend information provided by CPUE data. There are however options to change the status quo:

1. One is to explore the use of daily catch and/or landings information as a proxy for CPUE which may be useful in certain circumstances.
2. The other would be to identify a limited number of vessels which would provide reliable catch and landings and effort data, therefore providing a reliable and representative index of CPUE or LPUE for the resource.

This appendix addresses the first of these two options.

The basis for this section is the idea that even given the absence of detailed creel effort data, the daily catches may be a useful proxy for CPUE under certain circumstances. It is not uncommon, for example, in other jurisdiction, to make use of daily catch information as CPUE per se. Superficially this may seem to be an unlikely proposition, given that daily catch is potentially driven to a great extent by the number of creels hauled per vessel per day, in turn linked to vessel size and other parameters. Thus the nominal proxy for CPUE, daily catch, is probably influenced by a wide range of factors which make the daily catch from one year to the next incomparable and uninformative about the change in CPUE from year to year. For

example, we know that larger vessels can catch more and pull more creels per day, and also that soak time influences the catch, as do a myriad of other factors.

However, if one considers that vessels may generally work a similar average number of creels per day, and given the availability of modern statistical software which would allow the calibration of daily catch between vessels to be carried out as an automatic process within a GLM analysis (we explored the use of GLMMs with vessel ID as a random factor, but since the results are very similar to those obtained using GLMs, GLMs are used for the results reported here), there exists the potential that valuable resource abundance trend information could be extracted from daily and/or weekly catch logs.

Rather than leave this as is, there is an opportunity to test this proposition, since in one of the assessment areas relevant to this study, Shetland, detailed “creels hauled” data are available. So for this assessment area, it is possible to compare annual abundance indices that are calculated via GLM analyses using either daily catch or CPUE.

This appendix reports the results of GLM analyses which are carried out to this end. The data that were provided for this analysis were records of catch information on a “pull-by-pull” basis for crab and lobster, as follows:

- 44 697 records of catch data crab
- 44 056 records of catch data for lobster

The data contained in this dataset included the following

- Year of Catch
- Month of Catch
- Date of Catch
- Anonymized Vessel ID
- Number of Creels lifted
- Landings (kg)
- Vessel length (m)

In order to set these data up for GLM analyses, the following data pre-processing steps were implemented:

- 1) Aggregation to date x vessel ID level, summing up “Number of Creels Lifted” and “Landings (kg)”
- 2) Calculation of CPUE as = sum “Landings (kg)” / sum “Number of Creels Lifted”.
- 3) Calculation of Proxy lnCPUE = logarithm of (sum “Landings (kg)”)
- 4) Calculation of ln CPUE = logarithm of CPUE.

The factors that were used in the models were either Set A, B and C where Set A was:

- 1) Year (categorical variable)
- 2) Vessel ID (as a categorical variable)
- 3) Vessel Length (as a covariate)
- 4) Season (Q1, Q2, Q3 and Q4),

and Set B was the same as Set A but with the exclusion of the “Vessel ID” variable:

- 1) Year (categorical variable)
- 2) Vessel Length (as a covariate)
- 3) Season (Q1, Q2, Q3 and Q4)

Results are shown in the tables and figures below. Table 13.1 shows the GLM year factor results for Shetland lobster and crab, including Vessel ID as a factor in the GLM, for the GLM using variables ‘Set A’. A comparison of panels from left to right shows the comparison of the exponentials of the GLM year factors using either the CPUE based on catch/creel effort data (LH panel), or the CPUE represented simply as the daily catches. Table 13.2 provides corresponding information for the GLMs for ‘Set B’ where vessel ID has been excluded. Table 13.3 reports the unadjusted R^2 values for the GLMs. Table 13.4 provides the correlations between the year factors based on the CPUE with creel effort data and CPUE as daily catches, either in log-space or their exponentials. Figure 13.1 and Figure 13.2 provide a visual impression of these results, either as the two sets of year factors (based on the CPUE with creel effort data and CPUE as daily catches) plotted in exponentiated form versus year, or alternatively the exponential values plotted directly against each other.

In general these results show the following:

- 1) There is a very high correlation between the year factors produced using either the CPUE or the daily catches as the target variable for the analysis for the Shetlands. This suggests that the GLM analysis of daily catches has promise as a resource abundance index for other assessment areas for the Scottish inshore fisheries, to provide a stop gap resource abundance index pending the availability of more detailed creel effort information. This conclusion assumes that there is similar stability in the creel pulls per day per vessel as occurs for Shetland – informed input is required to confirm whether it is safe to make this assumption.
- 2) The inclusion of ‘Vessel ID’ in the GLM increases the unadjusted R^2 markedly. This is perhaps to be expected since there are in the order of 120 vessels in the dataset. Nevertheless in principle it is advisable to include Vessel ID in these GLMs in the event that they are used as the basis for an alternative resource abundance index.

It is clear that the use of these results to substantiate a recommendation that daily catches and/or landings can be used as a proxy for other assessment areas depends on the assumption that effort levels per vessel do not show an increasing or a decreasing trend. Indeed, this has not thus far even been demonstrated for Shetlands, let alone for other assessment areas. One would expect that, because of the agreement in year factor trends referred to above, effort (creels pulled per trip) are not systematically increasing or decreasing for the Shetlands. Some further analyses were carried out to verify that this is so. Results are shown graphically in Figure 13.3 to Figure 13.5.

Table 13.1 GLM year factor results for Shetland lobster and crab, including Vessel ID as a factor in the GLM. Left to right shows the comparison between using the creel effort data for CPUE, or simply the daily catches.

LnCPUE Lobster Only							LnCatch Lobster Only						
Year	Lower	Coefficient	Upper	Std. Error	t	Significance	Year	Lower	Coefficient	Upper	Std. Error	t	Significance
2006	-1,178	-1,113	-1,049	0,033	-34,049	0,000	2006	-1,058	-1,123	-0,742	0,033	-34,011	0,000
2007	-1,004	-0,943	-0,881	0,031	-30,207	0,000	2007	-0,929	-0,991	-0,612	0,032	-31,441	0,000
2008	-0,999	-0,937	-0,876	0,031	-29,806	0,000	2008	-0,813	-0,876	-0,572	0,032	-27,569	0,000
2009	-0,741	-0,685	-0,628	0,029	-23,835	0,000	2009	-0,542	-0,599	-0,238	0,029	-20,635	0,000
2010	-0,623	-0,568	-0,512	0,028	-20,068	0,000	2010	-0,493	-0,549	-0,098	0,029	-19,200	0,000
2011	-0,612	-0,556	-0,500	0,028	-19,537	0,000	2011	-0,464	-0,520	-0,161	0,029	-18,093	0,000
2012	-0,579	-0,523	-0,468	0,028	-18,542	0,000	2012	-0,449	-0,505	-0,207	0,029	-17,712	0,000
2013	-0,664	-0,608	-0,552	0,029	-21,236	0,000	2013	-0,502	-0,559	-0,301	0,029	-19,346	0,000
2014	-0,453	-0,398	-0,344	0,028	-14,311	0,000	2014	-0,341	-0,396	-0,129	0,028	-14,082	0,000
2015	-0,253	-0,198	-0,143	0,028	-7,075	0,000	2015	-0,137	-0,193	-0,040	0,028	-6,824	0,000
2016	0,000						2016	0,000					

LnCPUE Crab Only							LnCatch Crab Only						
Year	Lower	Coefficient	Upper	Std. Error	t	Significance	Year	Lower	Coefficient	Upper	Std. Error	t	Significance
2006	0,227	0,294	0,361	0,034	8,595	0,000	2006	0,149	0,219	0,289	0,036	6,136	0,000
2007	0,214	0,280	0,346	0,034	8,289	0,000	2007	0,111	0,180	0,249	0,035	5,111	0,000
2008	0,074	0,144	0,214	0,036	4,052	0,000	2008	0,035	0,108	0,181	0,037	2,907	0,004
2009	-0,050	0,018	0,086	0,035	0,512	0,609	2009	-0,075	-0,004	0,067	0,036	-0,110	0,912
2010	0,002	0,066	0,130	0,033	2,020	0,043	2010	-0,071	-0,004	0,063	0,034	-0,114	0,909
2011	0,018	0,083	0,149	0,033	2,495	0,013	2011	-0,048	0,020	0,089	0,035	0,580	0,562
2012	-0,188	-0,126	-0,064	0,031	-4,011	0,000	2012	-0,243	-0,179	-0,114	0,033	-5,446	0,000
2013	-0,064	-0,004	0,057	0,031	-0,116	0,908	2013	-0,077	-0,015	0,048	0,032	-0,460	0,646
2014	0,081	0,138	0,195	0,029	4,724	0,000	2014	0,017	0,077	0,136	0,030	2,527	0,011
2015	-0,024	0,036	0,095	0,030	1,175	0,240	2015	-0,101	-0,039	0,023	0,032	-1,238	0,216
2016	0,000						2016	0,000					

Table 13.2 GLM year factor results for Shetland lobster and crab, excluding Vessel ID as a factor in the GLM. Left to right shows the comparison between using the creel effort data for CPUE, or simply the daily catches.

LnCPUE Excl Vessel ID Lobster Only							LnCatch Excl Vessel ID Lobster Only						
Year	Lower	Coefficient	Upper	Std. Error	t	Significance	Year	Lower	Coefficient	Upper	Std. Error	t	Significance
2006	-1,131	-1,062	-0,992	0,035	-30,012	0,000	2006	-1,138	-1,068	-0,998	0,036	-29,841	0,000
2007	-0,973	-0,906	-0,839	0,034	-26,601	0,000	2007	-1,036	-0,969	-0,901	0,034	-28,110	0,000
2008	-1,025	-0,958	-0,891	0,034	-27,940	0,000	2008	-0,913	-0,845	-0,777	0,035	-24,372	0,000
2009	-0,692	-0,630	-0,567	0,032	-19,859	0,000	2009	-0,650	-0,587	-0,524	0,032	-18,298	0,000
2010	-0,587	-0,526	-0,465	0,031	-16,845	0,000	2010	-0,649	-0,587	-0,525	0,032	-18,580	0,000
2011	-0,640	-0,577	-0,515	0,032	-18,111	0,000	2011	-0,670	-0,607	-0,543	0,032	-18,806	0,000
2012	-0,641	-0,578	-0,515	0,032	-18,009	0,000	2012	-0,693	-0,630	-0,566	0,032	-19,385	0,000
2013	-0,750	-0,685	-0,619	0,033	-20,553	0,000	2013	-0,754	-0,688	-0,622	0,034	-20,410	0,000
2014	-0,523	-0,458	-0,394	0,033	-13,927	0,000	2014	-0,592	-0,527	-0,461	0,033	-15,824	0,000
2015	-0,286	-0,222	-0,157	0,033	-6,726	0,000	2015	-0,288	-0,223	-0,158	0,033	-6,691	0,000
2016	0,000						2016	0,000					

LnCPUE Excl Vessel ID Crab Only							LnCatch Excl Vessel ID Crab Only						
Year	Lower	Coefficient	Upper	Std. Error	t	Significance	Year	Lower	Coefficient	Upper	Std. Error	t	Significance
2006	0,221	0,312	0,404	0,047	6,686	0,000	2006	0,182	0,282	0,382	0,051	5,530	0,000
2007	0,130	0,222	0,315	0,047	4,718	0,000	2007	0,036	0,137	0,237	0,051	2,655	0,008
2008	0,077	0,175	0,273	0,050	3,508	0,000	2008	0,089	0,196	0,303	0,054	3,595	0,000
2009	-0,164	-0,069	0,026	0,049	-1,423	0,155	2009	-0,264	-0,160	-0,056	0,053	-3,013	0,003
2010	-0,057	0,034	0,125	0,047	0,733	0,464	2010	-0,248	-0,148	-0,049	0,051	-2,916	0,004
2011	-0,124	-0,030	0,064	0,048	-0,633	0,527	2011	-0,293	-0,190	-0,088	0,052	-3,636	0,000
2012	-0,650	-0,559	-0,468	0,046	-12,084	0,000	2012	-0,837	-0,738	-0,639	0,051	-14,604	0,000
2013	-0,460	-0,369	-0,278	0,046	-7,981	0,000	2013	-0,572	-0,473	-0,374	0,051	-9,364	0,000
2014	-0,135	-0,046	0,042	0,045	-1,026	0,305	2014	-0,315	-0,219	-0,122	0,049	-4,437	0,000
2015	-0,141	-0,049	0,043	0,047	-1,046	0,296	2015	-0,284	-0,183	-0,082	0,051	-3,557	0,000
2016	0,000						2016	0,000					

Table 13.3 Unadjusted R^2 values for the GLMs considered here, shown here as a % (of variance explained).

	GLM/Vessel ID		GLM/Vessel ID			
	Included -	Excluded -	InCPUE	InCatch	InCPUE	InCatch
Lobster	47%	49%	18%	22%		
Crab	70%	76%	19%	30%		

Table 13.4 Correlations between year factors or their exponents for different GLMs and species.

Model	With Vessel ID	Without Vessel ID
Year Factors		
Lob Only	0.9937	0.9849
Crab Only	0.9735	0.9775
Exp(Year Factors)		
Lob Only	0.9960	0.9906
Crab Only	0.9754	0.9707

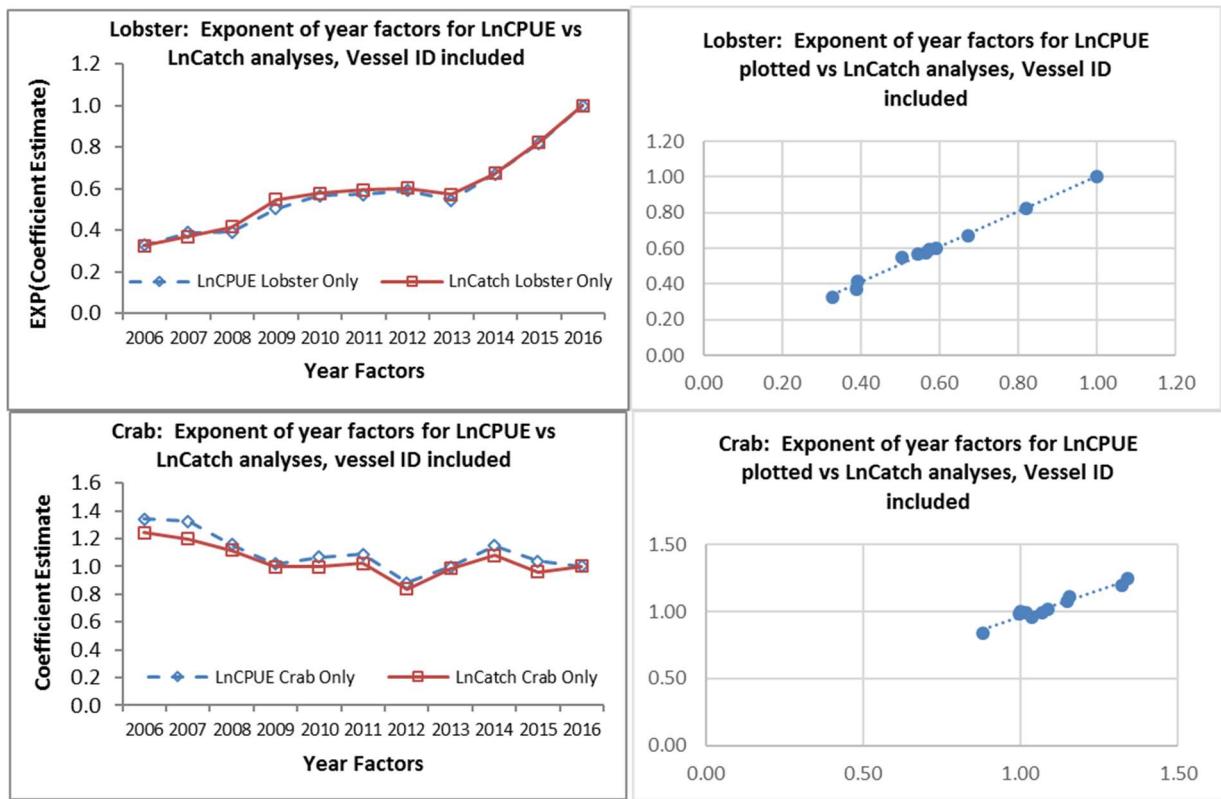


Figure 13.1 Various plots of GLM year factor results for Shetland lobster and crab, including Vessel ID as a factor in the GLM. The left-hand plot shows the exponentials of the year factors against time, while the scatter plots to the right show the year factors plotted against each other.

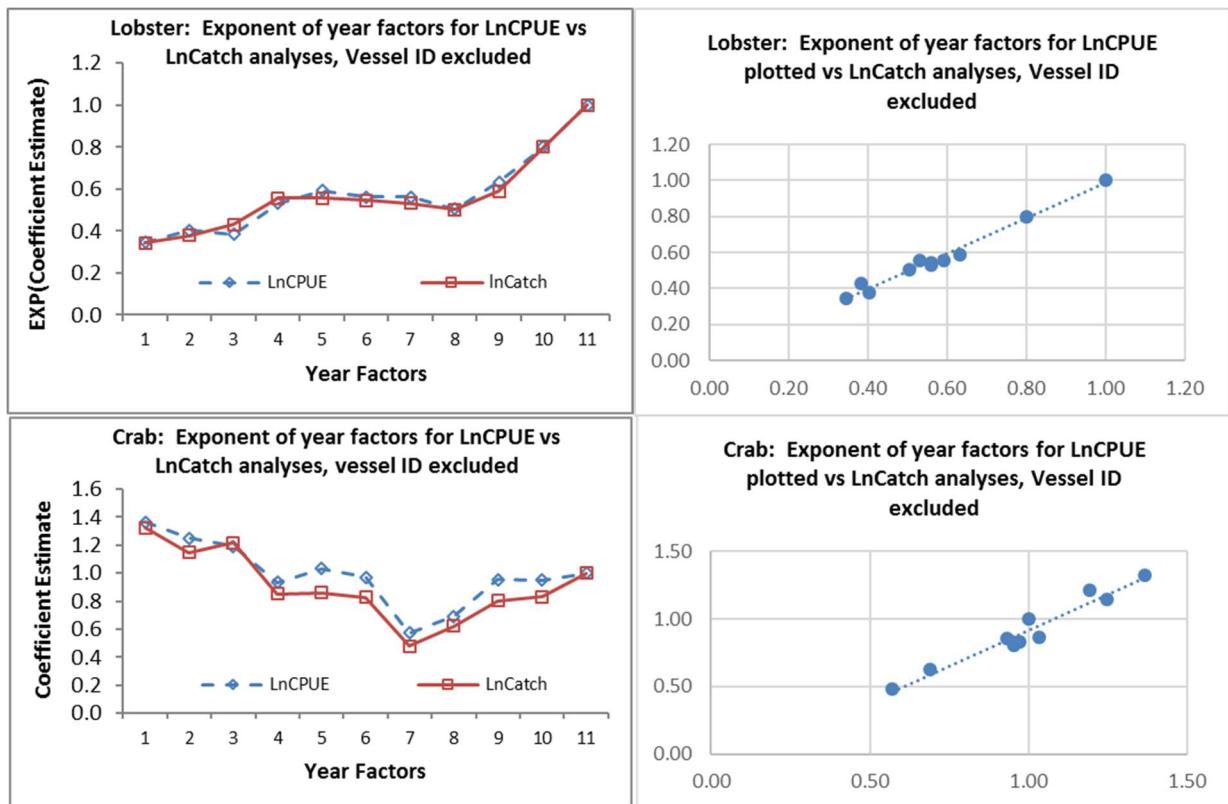


Figure 13.2 Various plots of GLM year factor results for Shetland lobster and crab, excluding Vessel ID as a factor in the GLM. The left-hand plot shows the exponentials of the year factors against time, while the scatter plots to the right show the year factors plotted against each other.

Table 13.5 A) Top panels shows the GLM year factor results for Shetland crab and lobster where Effort (No. Creels) is used as target variable and year, season and Vessel ID set as categorical factor variables. B) Bottom panels shows the GLM year factor results for Shetland crab and lobster where the natural logarithm of the Effort (LnEffort) is used as target variable and year, season and Vessel ID set as categorical factor variables.

Effort Crab							Effort Lobster						
Year	Lower	Coefficient	Upper	Std. Error	t	Significance	Year	Lower	Coefficient	Upper	Std. Error	t	Significance
2006	-15,283	-10,235	-5,187	2,576	-3,974	0,000	2006	-5,405	-1,662	2,080	1,909	-0,871	0,384
2007	-18,174	-13,179	-8,184	2,548	-5,172	0,000	2007	-8,018	-4,472	-0,926	1,809	-2,472	0,013
2008	-8,133	-2,873	2,388	2,684	-1,070	0,284	2008	5,393	8,984	12,574	1,832	4,904	0,000
2009	-9,834	-4,704	0,427	2,617	-1,797	0,072	2009	7,295	10,585	13,875	1,678	6,307	0,000
2010	-15,670	-10,833	-5,996	2,468	-4,390	0,000	2010	-1,150	2,101	5,351	1,658	1,267	0,205
2011	-13,755	-8,815	-3,875	2,520	-3,497	0,000	2011	0,103	3,361	6,619	1,662	2,022	0,043
2012	-12,918	-8,272	-3,626	2,370	-3,490	0,000	2012	-3,596	-0,374	2,849	1,644	-0,227	0,820
2013	0,030	4,551	9,072	2,306	1,973	0,048	2013	1,717	4,991	8,265	1,670	2,988	0,003
2014	-12,579	-8,277	-3,976	2,195	-3,772	0,000	2014	-3,311	-0,123	3,066	1,627	-0,076	0,940
2015	-18,425	-13,953	-9,480	2,282	-6,115	0,000	2015	-5,993	-2,764	0,465	1,647	-1,678	0,093
2016	0,000						2016	0,000					

LnEffort Crab							LnEffort Lobster						
Year	Lower	Coefficient	Upper	Std. Error	t	Significance	Year	Lower	Coefficient	Upper	Std. Error	t	Significance
2006	-0,101	-0,071	-0,041	0,015	-4,691	0,000	2006	-0,040	-0,014	0,013	0,013	-1,024	0,306
2007	-0,125	-0,096	-0,066	0,015	-6,398	0,000	2007	-0,078	-0,053	-0,028	0,013	-4,196	0,000
2008	-0,063	-0,032	-0,001	0,016	-2,013	0,044	2008	0,030	0,055	0,080	0,013	4,257	0,000
2009	-0,047	-0,017	0,013	0,015	-1,102	0,270	2009	0,051	0,074	0,097	0,012	6,313	0,000
2010	-0,094	-0,066	-0,037	0,014	-4,548	0,000	2010	-0,006	0,017	0,039	0,012	1,420	0,156
2011	-0,088	-0,059	-0,030	0,015	-3,986	0,000	2011	0,007	0,030	0,053	0,012	2,545	0,011
2012	-0,077	-0,049	-0,022	0,014	-3,553	0,000	2012	-0,007	0,016	0,038	0,012	1,352	0,176
2013	-0,035	-0,009	0,018	0,014	-0,649	0,516	2013	0,019	0,042	0,065	0,012	3,578	0,000
2014	-0,085	-0,060	-0,034	0,013	-4,625	0,000	2014	-0,030	-0,008	0,015	0,011	-0,659	0,510
2015	-0,098	-0,072	-0,046	0,013	-5,387	0,000	2015	-0,021	0,002	0,024	0,012	0,139	0,889
2016	0,000						2016	0,000					

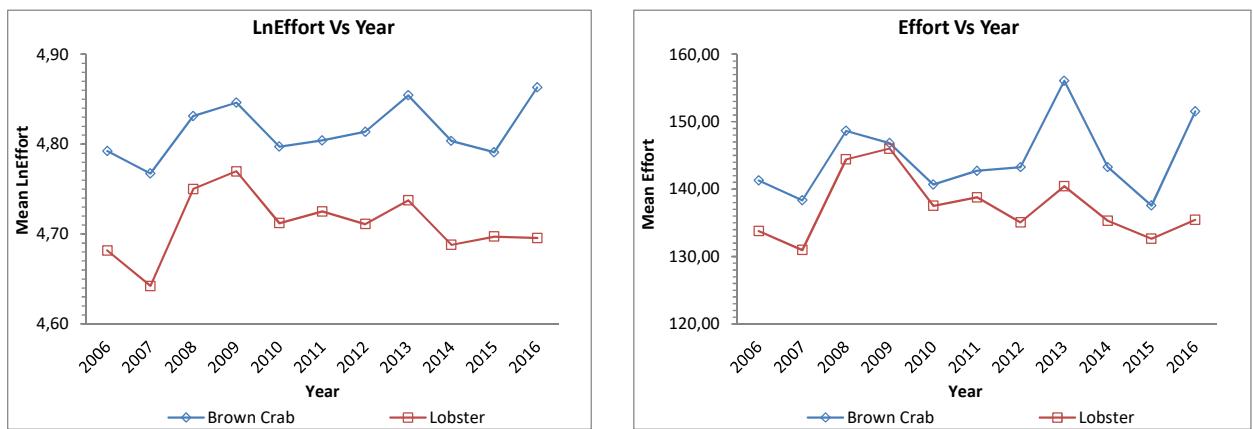


Figure 13.3 A) Left panel shows the plots of the estimated mean yearly effort (obtained from the GLMs where LnEffort was set as the target variable) versus year. B) Right panel shows the plots of the estimated mean yearly effort (obtained from the GLMs where Effort was set as the target variable) versus year.

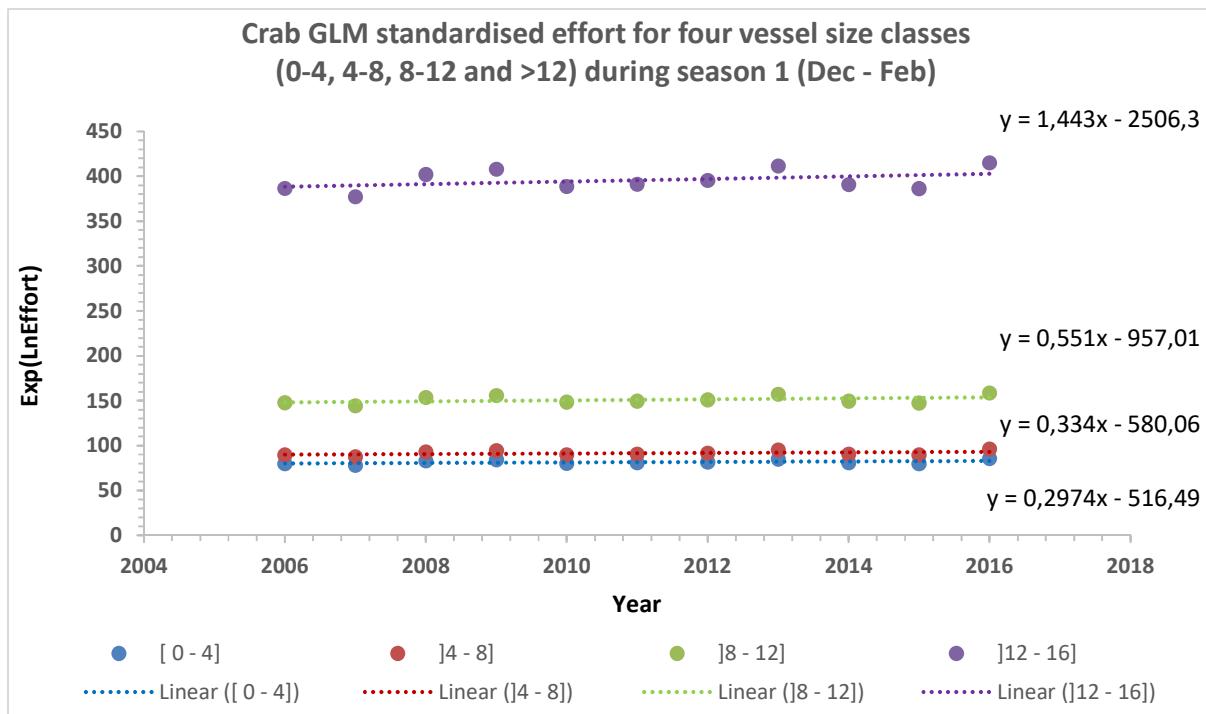


Figure 13.4 Standardised mean effort of four vessel length bin categories during season 1 (December to February) for brown crab.

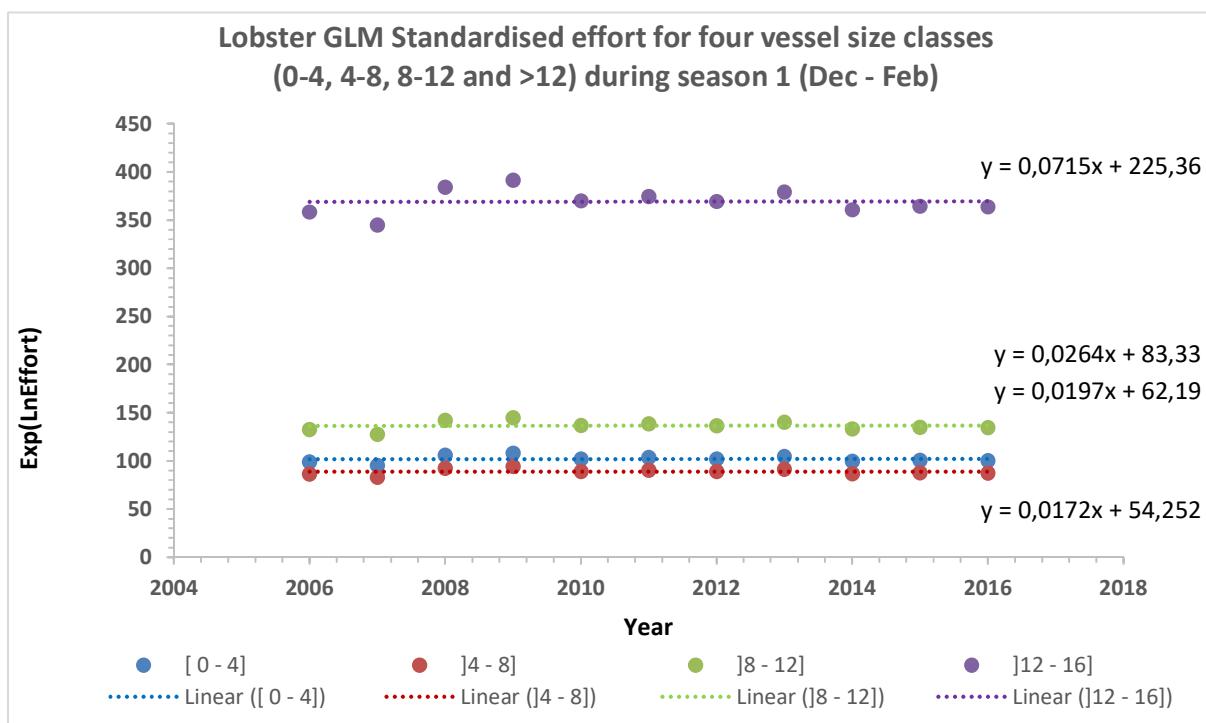


Figure 13.5 Standardised mean effort of four vessel length bin categories during season 1 (December to February) for lobster.

14 TECHNICAL APPENDIX 5

14.1 Optimisation sampling plans

This section addresses the problem of how to use the findings in this report to explore the costs and benefits of different sampling plans for the following sampling activities:

- Port sampling
- Observers sampling at sea
- Sentinel vessels involved in new technology based -sampling programmes
- Sentinel vessels involved in self-sampling programmes

We discuss initially an approach for port sampling, and then follow-up with suggestions for extending this to cover observer sampling programmes and sentinel vessels, either via self-sampling or observers. The suggestions made here focus on sampling to determine annual catch length frequency estimate.

One of the outputs from Technical Appendix 4 is a utility, which is available as a spreadsheet, and which calculates the variance of the length proportions (sex disaggregated) for a given sample derived from the landings of a particular trip. We will call this utility a Length Proportion Variance Calculator and abbreviate it LPVC.

In the main report, only idealised results are presented for the MWCV of the annual length proportions by assessment area, for given numbers of trips and animals sampled per trip. These calculations are presented separately for lobster, crab and scallops. These calculations do not cater for the following:

1. Sample size may or may not be controllable.
2. Lobster and crab would be sampled from the same vessel/trip.
3. Scallops would be sampled from different vessels and trips.
4. There are most likely logistical constraints on travel by samplers between ports.

The operationalisation of the LPVC involves using it to assess the statistical value of different sampling designs in relation to cost and logistic feasibility.

We assume the existence of a sampling plan. The sampling plan involves a grand total of N samples, $k=1, 2, \dots, N$, which are drawn from different vessels and trips at various ports during the year. Let a single sampling event be sampling the landings from a particular trip and denoted by $\text{SAMPLE}_{k,s,p,v,m}$. Apart from the index k (1,2,...,N), $\text{SAMPLE}_{k,s,p,v,m}$ is also indexed by s,p,v,m which are:

- s - Sampler
- p - Port
- v - Vessel Type, this would be crab/lobster, or scallops
- m - Month

We thus have a PLAN comprising a set of $\text{SAMPLE}_{k,s,p,v,m}$, $\text{PLAN}[\text{SAMPLE}_{1,s,p,v,m}, \text{SAMPLE}_{2,s,p,v,m}, \dots, \text{SAMPLE}_{N,s,p,v,m}]$. In practice a sampler will be located in a particular port on a given day and will need to apportion his/her sampling time for the day by sampling from a number of crab/lobster vessels or a number of scallop vessels. The following day the sampler will be directed to another port for sampling, or remain in the same port to continue sampling, or stop sampling.

Different PLANS can be assessed on the basis of cost, logistic feasibility and statistical merits. What makes sense is to start with a PLAN that is similar to or the same as the PLAN already in use. This plan would involve a logically feasible use of different samplers and a logically feasible sequence of deployment of samplers over time, ports and vessel types.

In order to estimate the statistical merits of a PLAN, each SAMPLE_{k,s,p,v,m} must be associated with a sampling outcome. A sampling outcome is the normalised length frequency for scallops if v = scallops, or the normalised length frequency for male and female lobster and male and female crab if v = lobster/crab. It is suggested that this association can be achieved by

- 1) Make a random draw with replacement from the set of available historical values for a particular port=p, vessel type = v and month = m. "Historical" should be limited to, say, the last five years. Do this for all samples, k=1, 2, ..., N.
- 2) The LPVC can now be applied to calculate a variance for each of the length proportions in the sample, noting that there are certain minimum and maximum cut-off sizes recommended for the use of LPVC, for the purpose of calculating the MWCV for the year. For length classes outside these ranges the proportion of catches is low and the variance estimates from LPVC are regarded as unreliable. The ranges are Lobster: 95, 100, ..., 125 mm; Crab: 145, 150, ..., 190 mm; Scallops: 100, 105, ..., 145 mm. Inputs to the LPVC are the number of animals sampled from each species and gender for each sample, and the catch length class proportions, for the range of length classes indicated.

We now assume the existence of a length frequency raising procedure. It is assumed that this length frequency raising procedure is a post-stratified calculation of overall mean length frequencies for each stock assessment area, for each year. This post-stratified calculation would typically involve the following steps (but the precise steps applied by MSS may differ, in which case the procedure described below would need to be modified), applied to each 5 mm length class:

- 1) Link each sample to its stratum.
- 2) Link each stratum to its stratum weight. The catch weight as landings for that year in that stratum would seem an adequate basis for determining stratum weights, and these are easiest expressed as proportions.
- 3) Calculate the normalised length frequency (i.e. length proportions) for each stratum as (a) the mean across each sample for each stratum, or (b) the catch weighted mean where in this case these catches are not the stratum catches but the trip catches for sampled trips, which are also best expressed as proportions.
- 4) Calculate the variances of the normalised length frequency for each stratum using formulae appropriate to (a) and (b). For (a) this is the sum of the variances divided by 4, for (b) it is the weighted sum of the variances, where these weights are the squares of the trip level weight proportions.
- 5) Calculate the stratified mean normalised length frequency (i.e. length proportions) for the year as the "sum product" of stratum weights and stratum means, across all strata.
- 6) Calculate the variance of the stratified normalised length frequency, as the "sum product" of the squares of the stratum weights and stratum variances.
- 7) Calculate the annual MWCV for the length frequency sample data. Although the basic formula for this is the square root of the stratified variance divided by the stratified mean for each length class, then multiplied by the stratified mean, summed over all length classes, this is equivalent to the sum of the square root of the variances over all length classes (since these variances are of a the proportion).

Repeat steps 1) to 9) more than 30 times to obtain an average value of the MWCV for a given management/stock assessment area, species, gender for a particular PLAN.

A given PLAN can now be characterised as follows:

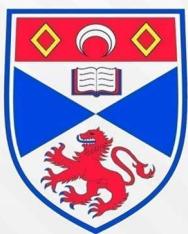
1. The number of stocks which exceed the statistical threshold of 30% w.r.t. MWCV.
2. Cost measured as number of sampler days plus travel costs and any other costs that go with a day of sampling such as per diems including accommodation costs. We are assuming here that if a sampler selects a port for sampling on a given day, that there will be landings available to be sampled, if not then a further factor and considerations will need to be built into the calculations.

Exploration of alternative PLANS, and improving the current best PLAN. Although the potential exists to model the problem of determining the optimal PLAN as a scheduling optimisation problem, this seems out of scope (and might in any case require the purchase of additional software such as CPLEX). We assume therefore that incremental improvements in the PLAN can be achieved in a heuristic fashion in which sampling in areas where the MWCV does not achieve its target threshold is increased (more trips), and reducing sampling effort where the target is well over-shot, taking note of the cost implications and the relative importance of different areas.

Adaptation for observer sampling: The above approach can be implemented for observer trips, using the same “random with replacement historical trip selection procedure” (on the assumption that an observer sampled trip has similar statistical properties as an observer sampled trip), with the added logistical constraint that an observer might be committed to more than one day at sea if a selected trip turns out to be a multi-day trip. Furthermore, it may be that observers at sea are able to measure more, or fewer, animals than port sampling, and this would have to be built into the assessment process.

Adaptation to cover the number of vessels in a sentinel fleet. The exploration of the pros and cons of the sampling plan for a sentinel fleet is possible, using a sampling plan which comprises all trips from a prospect set of vessels that form part of a prospective sentinel fleet. For the purposes of populating these trips (which were not all sampled historically), a combination of data from trips that were sampled, and the “random with replacement historical trip selection procedure” can be used, for a typical distribution of trips over time and ports. Whether all trips for these vessels can be assumed to be sampled depends on whether the technology in question permits this to be done cost effectively. For trips that are sampled as part of the sentinel fleet, an appropriate sample size per trip would be chosen, technology dependent, to form the basis for the MWCV calculations. As for the port sampling implementation, numerous runs of the model would be implemented to produce an average MWCV result.

Adaptation to cover self-sampling: This would follow a very similar approach as the previous application for a sentinel fleet.



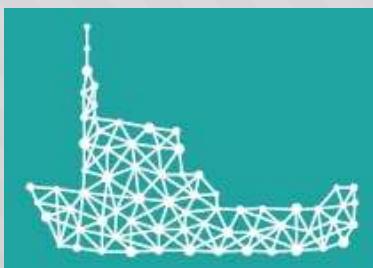
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