University of Strathclyde

Department of Mathematics and Statistics

Fleet dynamics in fisheries management strategy evaluations

Coby L. Needle

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Copyright declaration

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Statements on joint work

Section 6 is based on analyses first presented in Needle and Mosqueira (2011). My co-author in this paper (Iago Mosqueira, EC Joint Research Center, Ispra, Italy) has confirmed that the methods, results and analyses presented here are solely my own work.

Parts of Chapter III are based on the methodology and data analysis presented in Needle and Catarino (2011, reproduced in Chapter VI). My co-author in this paper (Rui Catarino, Marine Laboratory, Aberdeen) has confirmed that the methods, results and analyses presented here are solely my own work.

Signed:

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Contents

List of Figures

List of Tables

Abstract

Fisheries managers use scientific evaluations of management plans to determine whether such plans will be sustainable. Most extant evaluations do not account for changes in fleet dynamics in response to management measures, and are likely to be flawed as a result. In this thesis, I develop a new simulation model to address this issue. I present motivating case studies of management strategy evaluations for haddock, survey-based management approaches, and multi-species catch quotas, in order to highlight the need for an improved spatio-temporal fishery modelling framework. I characterise the response of the Scottish whitefish fleet to short-term real-time area closures, as an example of the type of fleet dynamics that a new model would need to be able to simulate for cod in the North Sea. I demonstrate using two complementary methods that such closures are unlikely to have directly encouraged skippers to avoid cod-important areas, and are therefore unlikely to have reduced cod mortality. I develop and implement a new spatio-temporal fishery simulation model which is flexible and powerful enough to account for fleet responses and thereby enable insightful quantitative analysis and evaluation of the wide range of management approaches. Finally, I report initial tests of the model, which demonstrate that a vessel seeking to maximise weekly profit will act differently (and with different fish stock implications) to one that is allowed a maximum weekly catch. With this model and the further future developments of it that I outline, scientists will be in a much better position to advise fisheries managers on stock sustainability over long-term time scales.

Chapter I

Introduction

1 The problem

In many parts of the world, agreements exist between different nations that allow their fishing fleets to participate in shared international fisheries. Some of these shared fisheries are also subject to shared management, in which governments meet to agree on how to regulate fishing effort, and how much effort to allow. A smaller subset of fisheries is subject to international fisheries management plans and harvest control rules, which seek to automate the management response to perceptions of stock dynamics (and thereby reduce the need for the long negotiations that can accompany the utilisation of any shared resource). For managers to be able to devolve much of their negotiating power, they must be confident that management plans will deliver what they expect (Kell et al. 2006); and in order to do this, plans must be tested. This can rarely be done experimentally in the field, so it is widely concluded (although not universally; see Rochet and Rice 2009) that management strategy evaluations (MSEs) must be conducted via computer simulations (Cooke 1999).

Many different frameworks exist to facilitate these simulations. Recent developments in Europe have included the FLR system (FLR Team 2006, Kell et al. 2007, Hillary 2009), which provides a suite of modules and libraries within the R statistical programming environment (R Development Core Team 2006); the Irish F-PRESS model (Codling and Kelly 2006, ICES 2007b) which is also based on R (but which has largely been superseded by FLR in the context of ICES advice); and the English SpatMan model (Bell et al. 2007). In the United States, parallel work at the National Marine Fisheries Service (NMFS) has produced the NOAA Fisheries Toolbox (NOAA 2008), while the EDON biological operating model has been used to model the effect of closed areas on the Californian coast (Walters et al. 2007). The problems evident in the management of valuable salmon stocks have also generated extensive work with MSEs and related analyses (for example, see Eggers 1992, Holt and Peterman 2006). Multispecies approaches which model predation as well as fishing have been developed, particularly for relatively simple boreal ecosystems (Hamre 2003), while multispecies models which consider only fleets fishing on two or more stocks (rather than predation links between the stocks) have been important in promoting the acceptance of management plans in a number of areas (Pilling et al. 2008). A body of literature has been developed on the analysis of risk in fisheries management, using MSEs as quantifying tools (see, for example, A'mar and Punt 2005, European Union 2009). Kruse et al. (2005) contains a number of relevant papers on management strategies and their evaluation in data-poor situations. The longest experience with MSEs, however, is to be found in Australia, New Zealand and South Africa (Butterworth and Punt 1999, Campbell and Dowling 2005, Hamon et al. 2007, Dichmont et al. 2008, Mapstone et al. 2008, Prince et al. 2008, Kolody et al. 2008, Butterworth 2008a, Smith et al. 2008, Dowling et al. 2008).

MSE simulations are generally designed around three distinct modules (Bunnefeld et al. 2011):-

1. A biological module, which generates the underlying populations and the effect of the fishery on them;

2. An assessment and advice (or knowledge production) module, simulating the advisory process including the same data collation procedures and assessment model as used by the relevant assessment working group (e.g. ICES 2008c); and

3. A management module, implementing the management rules.

These interact in an annual loop as shown in Figure 1.1, with additional initialisation and interpretation modules before and after the loop.

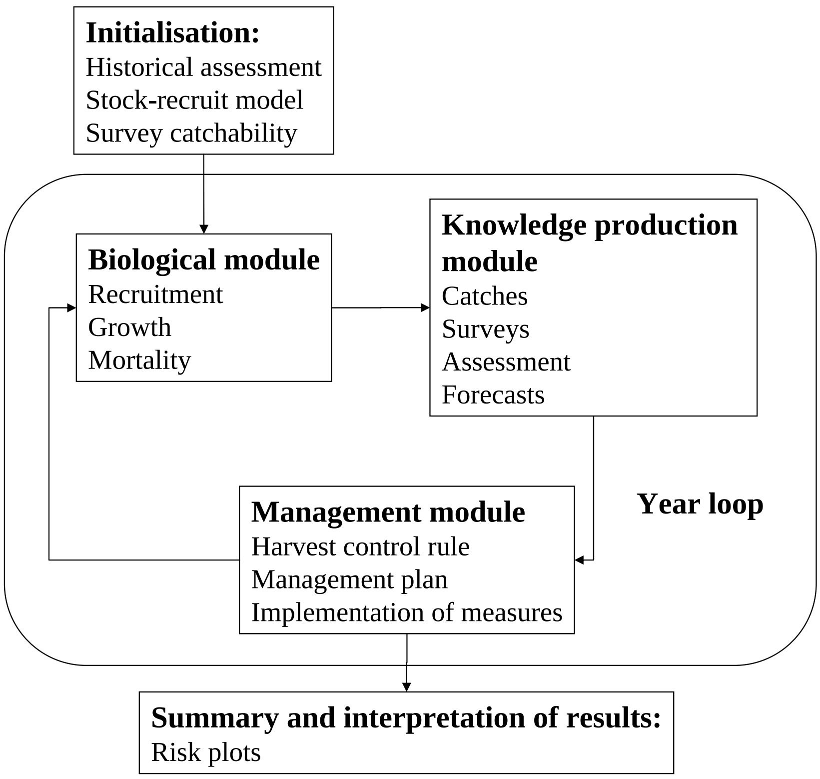


Figure 1.1: An example of an algorithm flowchart for fisheries management strategy evaluation (MSE).

MSE systems represent a substantial body of work and have been used for a number of years to provide scientific advice to fisheries managers on the likely utility of management plans and approaches that managers propose. In nearly all cases the effort has been worthwhile, in the sense that managers have been encouraged by the creation and scientific validation of management plans to attempt to move towards more sustainable fishery systems, to the extent that fishery MSE approaches are increasingly considered for management of terrestrial systems (Bunnefeld et al. 2011). However, considerable problems remain in three main aspects.

Firstly, most evaluations assume that the *responses of fishermen to management measures* are fixed for the foreseeable future, or are at least directly predictable. That is, a simulation will be carried out in which the relevant fishing vessels are expected either to carry on doing what they have been doing in the very recent past, or to modify their fishing patterns in very particular and forecastable ways. These expectations are seldom tested against observed data, with the result that simulations can deviate dramatically from reality. A successful fisherman is an intelligent businessman who will certainly modify fishing practice in response to management action if it appears beneficial to do so. In some cases, this can also be beneficial to the stock: Graham et al. (2007) discuss the changes in fishing practice brought about by a system of real-time area closures and a (somewhat loosely defined) discard ban in Norwegian fisheries. However, responses can also be deleterious to stocks, or can be driven to be either beneficial or not by the current state of the stock (for example, see Holt and Peterman 2006), and it is often difficult to know how to encode such changes in a computer simulation because it is often not clear what fishermen's motivations are. For example, a skipper who is trying to maximise profit may act quite differently in response to change than one who wishes to maximise catch, or minimise unwanted bycatch, or maintain a high social standing in his community (amongst other factors). Recently, Bastardie et al. (2010) incorporated skipper decision-making in their evaluation of a recovery plan for eastern Baltic cod, while Tserpes et al. (2009) considered the economic implications of a management plan for Mediterranean swordfish (although without modelling economically-driven changes in fleet responses). Branch et al. (2006) reviewed economic and sociological drivers of fleet dynamics in three classes of fishery: developing, mature and what they termed "senescent" (that is, almost exhausted). They found that very different suites of incentives and penalties were required in each class, and the use of the wrong approach at the wrong time (for example, subsidies in senescent fisheries) could be disastrous. However, the inclusion of such factors in evaluations has not often been attempted.

Secondly, few evaluations explore adequately the impact that fisheries managers can have on the development of a fishery. Managers are subject to a wide range of pressures, from the fishing industry, from environmental groups, from competing managers, from governments of their own and other countries, from scientists, and from the wider society. The means by which they reach their decisions and the principal drivers of change in their approach may be opaque, to say the least. Scientific advice may be followed to the letter, or it may be ignored, or it may be used as a bargaining chip to secure a better deal on some other issue altogether. The advice itself may be of relatively low quality and fluctuate from year to year, reducing confidence (Sparholt 2001, Sparholt and Bertelsen 2002, Bertelsen and Sparholt 2002). Managers can change their approach from year to year for reasons which are not always clear. The existence of agreed management plans should serve to restrict the ability of managers to sidestep conservation criteria, and in theory it should be reasonable for a scientist conducting an MSE to assume that the "virtual" managers within the simulation are similarly restricted. This is just another assumption, however, and should be subject to the same testability criteria that is needed for assumptions about fishermen's activities.

It is also clear that uncertainty in assessments and advice can hinder managers considerably in their attempts to achieve their objectives. Thinking about knowledge and its precision in fisheries management science during development of this thesis generated the following questions, which one would hope could be addressed following the development of an appropriate management evaluation structure:

1. How does the robustness of different assessment management approaches depend on sources of uncertainty?

2. What is the smallest amount of information on which successful fisheries management can be based?

3. What must fisheries managers know?

4. What are the important sources of error and uncertainty?

These are valuable points to bear in mind throughout this thesis, and I will return to them in Chapter V to see if they can yet be answered or not.

Thirdly, most evaluations to date have been based on very simple representations of marine biology and ecosystem function. For example, the mean fish weight-at-age and proportion mature-at-age may be assumed to be fixed in the simulation (so that there is no variation in growth or condition). Changes in the shape and spread of length distributions-at-age may similarly be ignored. Recruitment may be generated via poorly-defined stock-recruitment relationships, or using empirical time-series characterisations with little actual consideration for underlying biological process. Crucially, few evaluations have included models of multispecies interations (Mueter and

Megrey 2006, Pilling et al. 2008): the main exceptions to this have been simulations of Arctic or boreal fisheries with naturally simple ecosystems (e.g. Hamre 2003). The effects of observed and predicted climate change are further complications that have seldom been considered. It is true that there may be good reasons for not modelling ecosystem change in too much detail. In many cases the processes linking a measurable environmental effect with subsequent population dynamics are unknown or difficult to test; it can also be the case that the inclusion of environmental effects in management advice (if done incorrectly) can make such advice worse (Basson 1999). On the other hand, *not* considering ecosystem effects when these are known to be changing in ways that will affect fisheries is also an error (Cook and Heath 2005, Beaugrand et al. 2003), and there is clearly a balance to be struck.

For a management strategy evaluation to be able to provide useful and pertinent information on the likely outcome of management action, it needs to characterise these three aspects *to the extent necessary* to address the question being asked (Harte 1988). The availability of powerful computers should not be viewed as an incentive to try and include every conceivable (and perhaps even measurable) driving force in the evaluation, and properly-constructed yet relatively simple models have a powerful role to play. Paola (2011) described the historical reliance on simpler models in the absence of high computational power thus:

> It cultivated an essential counterpart to attention to detail, which is attention to what is truly essential.

And concluded that:

> The danger in creating fully detailed models of complex systems is ending up with two things you don't understand - the system you started with, and your model of it.

The complex multispecies models required for a mixed fishery in the North Sea, for example, would be of a quite different order to the relatively simple models required for a directed cod fishery in the Arctic Ocean, because the latter is a simpler ecosystem with fewer species than the former. A system in which managers are tightly constrained by a legally-defined management plan framework has less need of an evaluation which models managers' responses to change, than one in which management action is subject to re-negotiation each year. And the degree to which fleet dynamics need to be included is dependent on how free fishermen are to choose different actions (and on how much data are available to characterise those actions).

In this thesis, I will develop case studies and modelling frameworks that attempt principally to explore the first of these aspects: fleet dynamics and responses to management measures. The frameworks thus generated will be applicable to the second and third aspects also, but the full development of these will be left mostly to future work.

2 Influences on fisheries

In this thesis, Chapter II presents methods and results for a series of case studies of management strategy evaluation (MSE). These examples will demonstrate that, in order to be appropriate, management strategy evaluations must characterise the key features of the fishery system *to the extent necessary* for relevant management advice. These features will not be the same for every system, and nor will the amount of detail required. For example, the main feature missing from the existing North Sea haddock MSE (Section 4) is an appropriate model of discarding behaviour. On the other hand, current survey-based management evaluations (Section 8) will be hindered if the way in which real surveys do not always cover the full stock distribution (due to unfishable areas, say) is not adequately represented: fleet behaviour is much less relevant in this case. The goal of any good evaluation should be to incorporate those aspects pertinent to the advisory context.

Figure 2.1 provides a suggested influence diagram for a typical fishery. There are three levels to this, indicated by concentric ovals in the Figure. The inner level contains the processes which are key to any managed fishery, and which may need to be modelled dynamically and in considerable detail: *fisheries*, *managers* and *ecosystems*. There are links between these: strong influences of managers and ecosystems on fisheries, and of fisheries on ecosystems; and potentially weaker influences of fisheries and ecosystems on managers.

The intermediate level includes processes which are influential for (and which are potentially influenced by) processes in the inner level. For example, the decisions of *banks* on whether or not to grant skippers loans to build new vessels is a crucial business influence that affects the development of the fleet. Pressure from banks to maintain loan repayments is also a key driver in the fishing decisions of many skippers (Cox and Schmidt 2006). The relationship does not only operate in one direction, however: the performance of the fishery (and the individual vessels therein) will determine whether the bank is willing to invest in it (and them). Fish prices offered by the *market* are likely to be another key driver for many vessels, but here again skippers can have an influence in that a glut in landings of a particular species can have strong effects on the market value of that species (for example, Vignes and Etienne 2011). The wider *society* may have different perceptions of fishermen at different times, ranging from the romantic view (noble hunters) to the disparaging (environmental despoilers), and these may have concomitant effects on how fishermen perceive themselves, and on their subsequent activities (Oliver 2005). Fishermen, of course, are also members of society and have an influence on these perceptions (WorldFishingToday.com 2008).

The concerns of society may have an effect on fisheries managers through (for example) environmental pressure groups (Oceana 2011). Finally (in this scheme), governments do not affect and are not affected by fishermen directly, save that any member of the voting public has some influence on their government – most of the relationship between government and fisheries is channelled through fisheries managers (although these may also be members of the government). Processes in this intermediate layer need to be modelled dynamically, but this modelling can be at a coarse level only.

The outer layer in Figure 2.1 contains processes which clearly have an effect on fisheries, managers or the ecosystem, but which are not affected directly by them. Examples are *fuel price and availability*, which can serve as a strong limitation on fishing but which cannot really be influenced by the fishermen themselves, and *climate change* which drives ecosystems but which cannot be readily be moderated by human action on the time scale usually considered in fisheries management strategy evaluations. These outer-level processes can generally only be modelled in terms of scenarios.

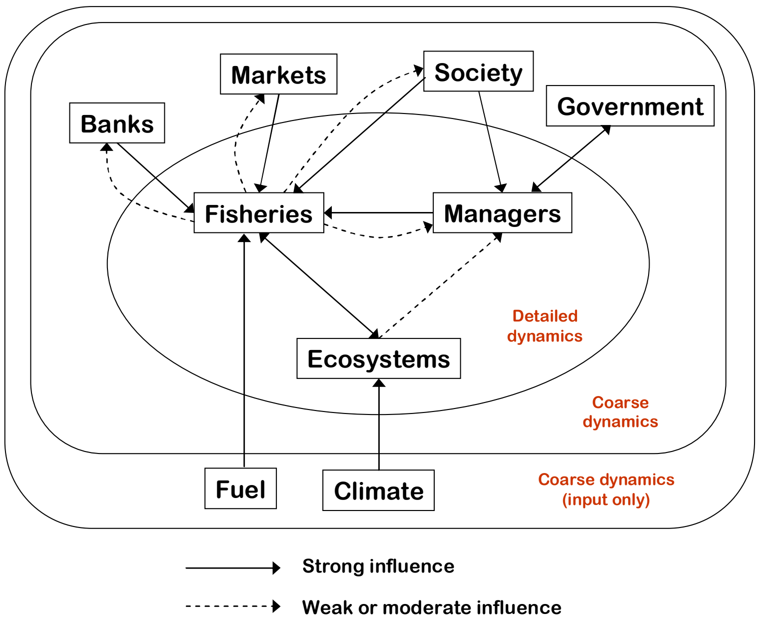


Figure 2.1: Initial suggestion for a generic influence diagram for fisheries.

These are just a few examples of the many external factors which may influence fishery decision-making: there are many others. The main point is this: the key stage of the development of a fisheries MSE is the appropriate determination and characterisation of the germane factors for the particular situation being considered. If this is done incorrectly, then any subsequent advice on management is likely to be flawed and may impinge on the sustainability of the stock(s) and the fishery. In this thesis, I will develop a new simulation model to address the potentially important issue of fleet behaviour in particular. I will present five motivating case studies to highlight the need for an improved spatio-temporal fishery modelling framework. I will then characterise the response of the Scottish whitefish fleet to real-time closures, as an example of the type of fleet dynamics that a new model would need to be able to simulate for cod in the North Sea, and will demonstrate using two complementary methods that such closures are unlikely to reduce cod mortality. Finally, I will develop, implement and test a new spatio-temporal fishery simulation model which is flexible and powerful enough to account for fleet responses and thereby enable insightful quantitative analysis and evaluation of the wide range of management approaches.

3 Thesis plan

The plan of this thesis (Table 3.1) is based on considerations of the influence diagram in Figure 2.1 and, in turn, the motivating examples in Chapter II. The ultimate goal of this work is the creation, testing and dissemination of a general, spatially-structured, multi-species simulation model of fisheries, management and ecosystems within which a wide range of management approaches and strategies can be evaluated. This full goal was not achievable within the time-scale of this doctorate, however, so what follows is a plan for producing a series of key modules for this general model. The modules themselves may appear somewhat disparate, but the intention is that they will feed into the same overarching structure. I have also included facsimiles of two published papers on which certain Sections were based, namely Needle (2008c, for Section 4) and Needle and Catarino (2011, for Sections 11 and 13): these are reproduced in Chapter VI.

Chapter I: Introduction

Chapter II: Motivating examples

1. Management strategy evaluation for North Sea haddock
2. Management strategy evaluation for West of Scotland haddock
3. Management strategy evaluation for Rockall haddock
4. Quota points
5. Survey-based assessment models

Chapter III: Characterising fleet dynamics

1. Background
2. Developing a relative index of fish importance
3. Data for analysing fleet dynamics
4. Fleet responses to real time closures
5. Effects on individual skippers of closures
6. Conclusions

Chapter IV: A general simulation model

1. Spatio-temporal fishery simulation models
2. Representing space
3. Generating a simulated area
4. Path finding
5. Representing fish populations and fishing vessels
6. Testing the simulation model
7. Future work

Chapter V: Conclusions

Chapter VI: Published papers

Chapter VII: References

Table 3.1: Thesis plan.

Chapter II

Motivating case studies

4 Management strategy evaluation for North Sea haddock

This section is based on a series of analyses carried out to inform European fisheries managers on the likely efficacy of a number of proposed management plans for the North Sea haddock stock. The summary given here follows closely that in Needle (2008c), but relevant material and development work is also given in Needle (2006a, 2006b, 2006c, 2008a, 2008b) and ICES (2006b, 2006a, 2006c, 2007b, 2008a). In the wider context of the thesis, my intention here is to demonstrate the problems that can arise with fisheries modelling if possible changes in fisheries activities (in this case, discarding practices) are not taken into account.

4.1 Background

The North Sea haddock (*Melanogrammus aeglefinus*) stock is exploited both by European Union (EU) member states and by Norway, and is managed as a shared stock (Figure 4.1). In 1999 the EU and Norway agreed the terms of a management plan for haddock, which was finally implemented in January 2005. The main elements of the plan were twofold:

1. Management regulations should seek to achieve a target fishing mortality F_{target} of 0.3.

2. Spawning-stock biomass (SSB or B) should be kept above the precautionary level ($B_{\text{pa}} = 140$kt). If B falls below B_{pa}, additional measures should be taken to ensure that B increases.

Here, fishing mortality $F_{a,y}$ for age a and year y is defined by the following relationship:

$$F_{a,y} = \ln\left(\frac{N_{a,y}}{N_{a+1,y+1}}\right) - M_{a,y}, \tag{4.1}$$

where $N_{a,y}$ is fish abundance in the stock, and $M_{a,y}$ is the estimated (or assumed) natural mortality. F_{target} is then the average of $F_{a,y}$ for a predefined range of ages (2 to 4 for North Sea haddock). Spawning-stock biomass in year y is defined by:

$$B_y = \sum_a N_{a,y} W_{a,y} \text{Mat}_{a,y}. \tag{4.2}$$

This is the total weight of sexually-mature fish in the population: $W_{a,y}$ is the estimated mean weight of fish aged a in year y, and $\text{Mat}_{a,y}$ is the proportion of these fish that are estimated to be mature.

The management plan contained a clause specifying that a review was to be carried out by the end of 2006. In April of that year, the EU and Norway approached the International Council for the Exploration of the Seas in Copenhagen (ICES) to inquire about the feasibility of addressing this review through ICES assessment working group channels. It was agreed that the ICES Working Group for the Assessment of Demersal Stocks in the North Sea and Skagerrak (WGNSSK) would coordinate the evaluation of the existing plan and any proposed modifications, and that the review would be prepared subsequently during the October 2006 meeting of the ICES Advisory Committee for Fisheries Management (ACFM).

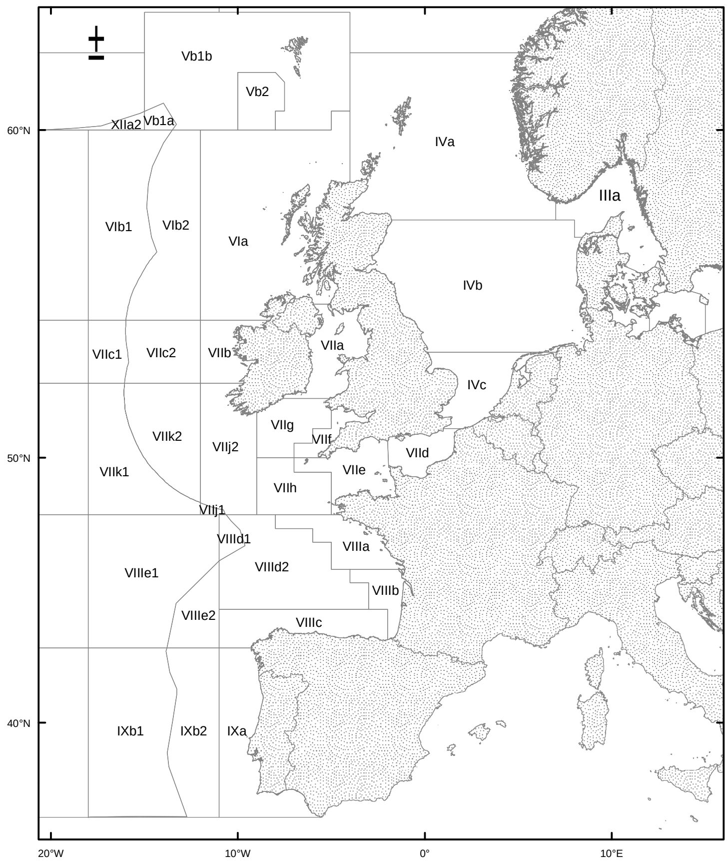


Figure 4.1: ICES sub-areas and divisions for Western Europe. The management area for North Sea haddock consists of Sub-Area IV (a, b and c) and Division IIIa (Skagerrak). Note that the Skagerrak is the north-western part only of Division IIIa, immediately to the north of Denmark. Source: `http://www.ices.dk`.

I presented initial analyses (Needle 2006a) in June 2006 at the ICES Working Group on Methods of Fish Stock Assessment (ICES 2006c), at which improvements and modifications were suggested. Consultations with managers and stakeholders followed, and updated results (Needle 2006c) were discussed at the October meeting of ACFM (ICES 2006a). The new analyses formed the basis of ICES advice to the EU and Norway which was presented at their annual bilateral negotiations in November 2006. In the margins of these meetings further discussions were held on the likely sustainability of the proposed plan, and this led to modifications (the addition of a sliding-F rule, and the clarification of the time when biomass should be measured). Following this process, the revised plan came into force on 1st January 2007. The methodology and results of the evaluation on which this decision was based were written up and published in Needle (2008c, and reproduced in Chapter VI).

4.2 THE EU-NORWAY MANAGEMENT PLAN

The text of the plan as implemented in 2007 is as follows.

1. Every effort shall be made to maintain a minimum level of Spawning Stock Biomass greater than 100,000 tonnes (B_{lim}).

2. For 2007 and subsequent years the Parties agreed to restrict their fishing on the basis of a TAC consistent with a fishing mortality rate of no more than 0.3 for appropriate age-groups, when the SSB in the end of the year in which the TAC is applied is estimated above 140,000 tonnes $\left(B_{\text{pa}}\right)$.

3. Where the rule in paragraph 2 would lead to a TAC which deviates by more than 15% from the TAC of the preceding year the Parties shall establish a TAC that is no more than 15% greater or 15% less than the TAC of the preceding year.

4. Where the SSB referred to in paragraph 2 is estimated to be below B_{pa} but above B_{lim} the TAC shall not exceed a level which will result in a fishing mortality rate equal to $0.3 - 0.2 \times \left(B_{\text{pa}} - SSB\right) / \left(B_{\text{pa}} - B_{\text{lim}}\right)$. This consideration overrides paragraph 3.

5. Where the SSB referred to in paragraph 2 is estimated to be below B_{lim} the TAC shall be set at a level corresponding to a total fishing mortality rate of no more than 0.1. This consideration overrides paragraph 3.

6. In order to reduce discarding and to increase the spawning stock biomass and the yield of haddock, the Parties agreed that the exploitation pattern shall, while recalling that other demersal species are harvested in these fisheries, be improved in the light of new scientific advice from *inter alia* ICES.

7. In the event that ICES advises that changes are required to the precautionary reference points Bpa (140 000 t) or B_{lim} (100 000 t) the Parties shall meet to review paragraphs 1-5.

8. No later than 31 December 2009, the Parties shall review the arrangements in paragraphs 1 to 7 in order to ensure that they are consistent with the objective of the plan. This review shall be conducted after obtaining *inter alia* advice from ICES concerning the performance of the plan in relation to its objective.

In essence, the plan can be simplified to two key points:

$\mathbf{F}_{\text{target}}$ and TAC constraint Set the Total Allowable Catch (TAC) in the quota year (that is, the year after the assessment) so that the expected fishing mortality rate when the TAC is taken is $F_{\text{target}} = 0.3$, where F_{target} is the intended mean fishing mortality over some pre-specified age range (ages 2–4 for North Sea haddock), as long as this results in spawning-stock biomass $B > B_{\text{pa}}$ at the beginning of the first year after the quota year. B_{pa} is defined as the precautionary level of biomass below which the stock should not fall. Modify the TAC to ensure that the maximum inter-annual change in TAC is $\pm 15\%$. Note that, although "catch" is referred to in the text of the plan, it is really landings that are controlled.

Sliding-*F* rule If, following the application of the $F_{\text{target}} = 0.3$ above, $B < B_{\text{pa}}$ in the first year after the quota year, apply the sliding-F rule with no TAC constraint (Figure 4.2). This is analogous with the target harvest rule commonly used in salmon fisheries (Butterworth and Punt 1999, Holt and Peterman 2006), in which the target F is a nonlinear function of forecasted recruitment, and can be seen as a simplified version of the generic rule proposed by Froese et al. (2011, see Figure 1).

The first point ensures that management decisions are based on predictions of the *results* of management actions; the second is intended to prevent a strict adherence to a pre-defined F_{target} in situations where it is clearly no longer appropriate. However, these two features make evaluation of the plan quite complicated. It is easy to envisage a situation in which the forecast at $F_{\text{target}} = 0.3$ leads to a biomass after the quota year which is between B_{lim} and B_{pa}. In this case the sliding-F rule stipulates a different F_{target} (Figure 4.2), so the forecast must be performed again – which leads to another different F_{target}, and so on. This cycle converges to a single solution, but only at the cost of computational complexity and potentially long run-times.

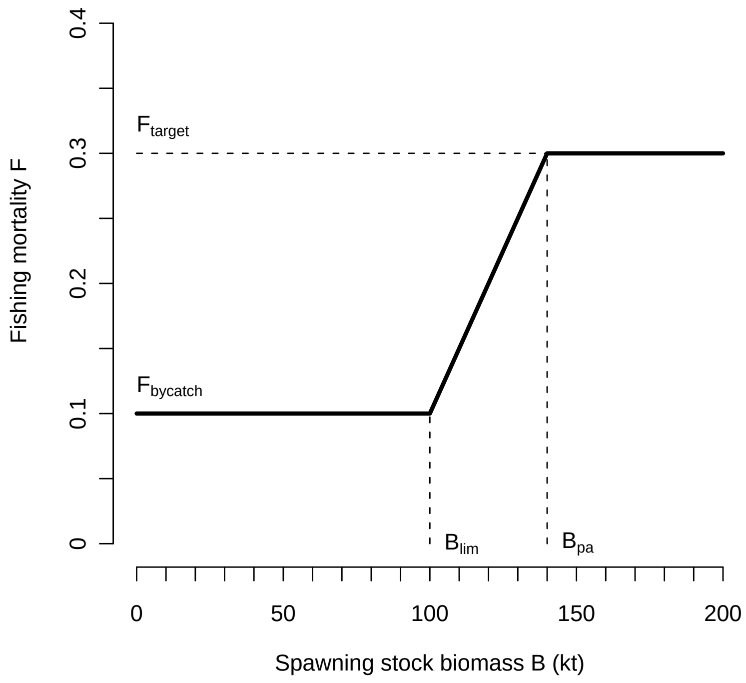


Figure 4.2: The sliding-F rule (thick line) for specifying the intended fishing mortality rate $\tilde{F}$ (see page 25), based on the expected spawning-stock biomass B remaining after the corresponding quota has been taken. For North Sea haddock: $F_{\text{target}} = 0.3$, $F_{\text{bycatch}} = 0.1$, $B_{\text{lim}} = 100$ kt and $B_{\text{pa}} = 140$ kt.

The procedure is laid out schematically in Figure 4.3, while the timeline of events considered by the management plan is laid out in Figure 4.4. The plan can be categorised as an F-based harvest control rule, in which F_{target} for a particular year is specified by the expected biomass that would be left in the stock after the application of that F_{target}. The plan is also restricted to the use of quotas (rather than effort limits or technical measures) as the management tool.

Figure 4.3 shows an additional step in the simulated plan that is not present in the actual plan, namely the limit of interannual change in F_{target} to $\Delta F = \pm 25\%$. This must be included in the simulation model to prevent the rapid (and irreversible) increase in F_{target} that can occur when managers try to maintain quotas in the face of a long series of low recruitments. Although essential to prevent the possibility of simulation failure, in practice it is seldom needed for the North Sea haddock evaluation.

The management plan came under scrutiny again in 2008, following a meeting in Bergen in June of the EU-Norway Working Group on Inter-Annual Quota Flexibility. This had been convened as a result of a number of requests by EU member states that they be allowed to manage their quotas of a number of shared stocks (including North Sea haddock) allowing for inter-annual quota flexibility: that is, the potential

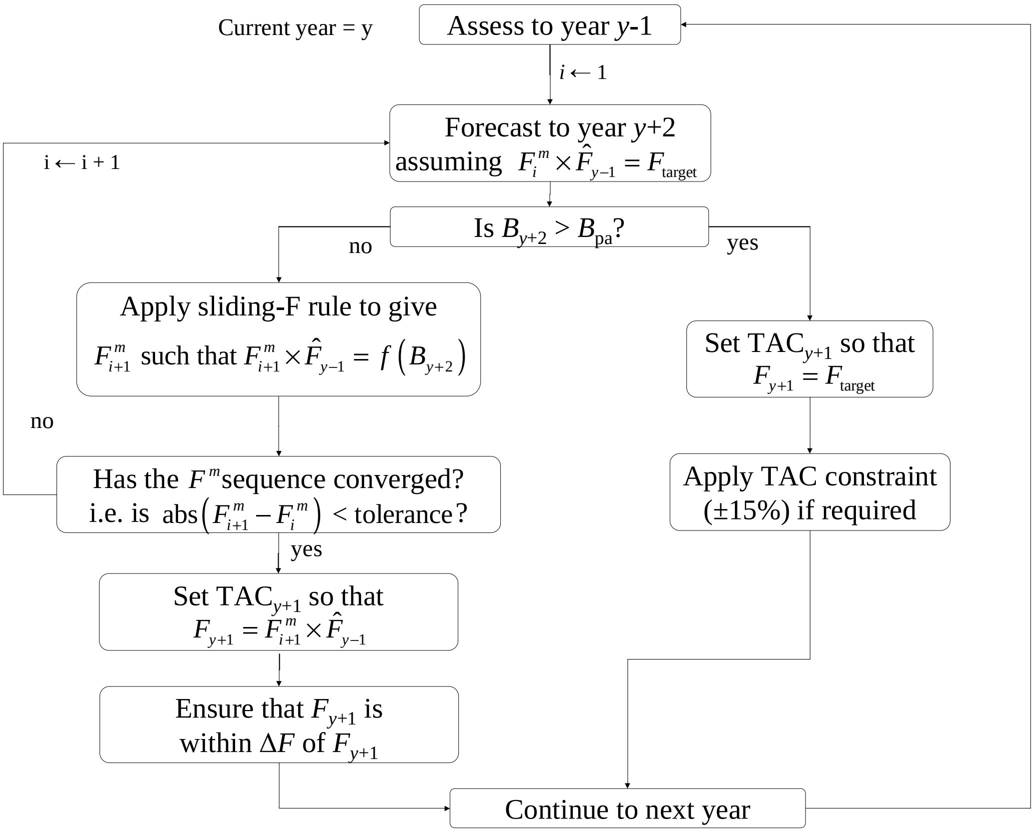


Figure 4.3: Flowchart outlining the key points of the North Sea haddock management plan. See text (page 23) for notation. Note that $f\left(B_{y+2}\right)$ is shorthand for "the sliding-F rule applied to biomass in the year $y+2$".

for some of this year's quota to be *banked* (taken from the year's quota and added to next year's) or *borrowed* (taken from next year's quota and added to this year's). This was allowed for stocks wholly managed by the EU, but not (at the time) for stocks shared with Norway. One of the objections raised by Norway was that the sustainability implications of quota flexibility had not been adequately evaluated, and the Working Group was convened to consider this.

At this meeting, I presented the existing flexibility proposal (Stuart 2007) in the form of an algorithm that could form the basis of a subsequent numerical evaluation, and also showed the effect of the proposal when applied to a highly simplified example (Needle 2008a). The stipulations of the proposal were:

1. A maximum flexibility of $\pm 10\%$ will apply.
2. The stock must be predicted to remain above B_{pa} in the year following the year in which the TAC is applied.

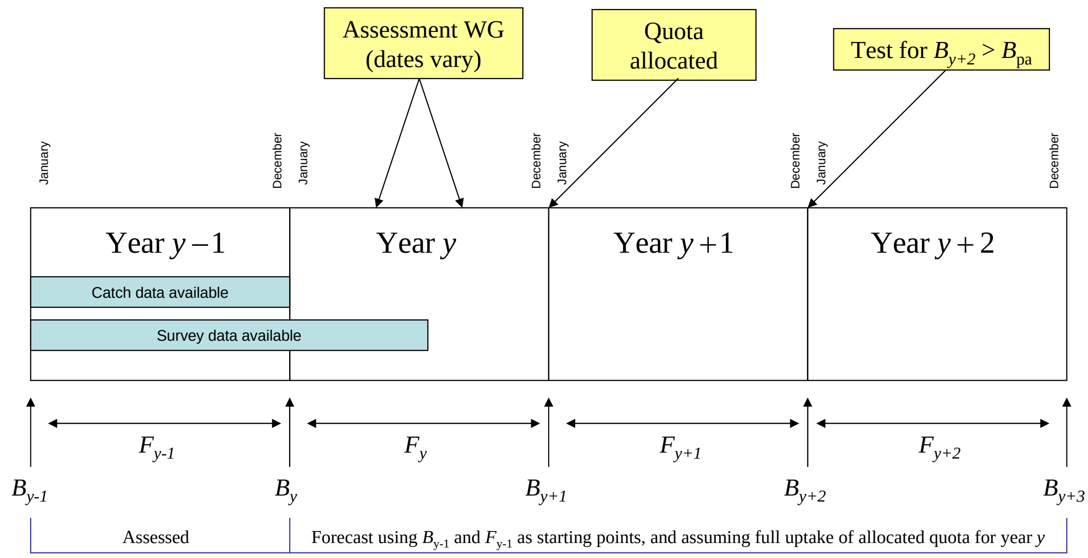


Figure 4.4: A timeline showing the sequence of events in one application of the proposed North Sea haddock management simulation. If the assessment WG meets in year y, then complete catch data are available for years up to and including $y-1$, while survey data may additionally be available for year y depending on when the WG meets. The required output from the process is an estimate of catch in year $y+1$, and SSB at the start of year $y+2$ (which we denote by B_{y+2}).

3. Quota banked for next year, or borrowed from next year, is not available for subsequent banking or borrowing.

The Working Group decided that an evaluation would be carried out during the summer of 2008, based on the evaluation framework developed by Needle (2008c) and modified to incorporate the changes proposed in Needle (2008a). Following an email exchange in July 2008, it was decided furthermore that the evaluation should be conducted under the auspices of the Advisory Committee (ACOM) of ICES, using the same Terms of Reference. The full results of this evaluation are given in Needle (2008b), and are discussed further below.

4.3 Evaluation methods

The evaluations carried out during this work have required the generation of computer code of considerable complexity. The code is written in R (R Development Core Team

2011, version 2.8.1) using modules and functions from the FLR library (FLR Team 2006, Kell et al. 2007, Hillary 2009, `http://flr-project.org/`), along with calls to functions written in Fortran-90 to improve run speed. The key elements included are as follows (taken from the Appendix of Needle 2008c, see also Chapter VI).

Structure

For North Sea haddock, the basic MSE structure followed that outlined in Figure 1.1. 50 (Needle 2008c) or 100 (Needle 2008b) simulations were run, each for 20 or 25 years into the future, and for a series of scenarios with different F_{target} values (from 0.1 to 0.5 in steps of 0.1) with interannual quota variability set to $\pm 15\%$. Through each simulation, two separate stock data streams were maintained: one containing *true* information on stock dynamics (abundance, mortality etc), and one giving the *assessed* stock information as would be available to managers in reality. As I discuss below, these two stocks (true and assessed) can be quite different, and the differences between them can be very influential on the outcome of the evaluations. Outcomes were expressed in terms of the percentage of years in each simulation for which spawning stock biomass B fell below the defined precautionary $\left(B_{\text{pa}}\right)$ or limit (B_{lim}) biomass reference points.

Historical data and parameter setting

Estimated numbers-at-age and mean weights-at-age for three catch components (landings, discards and industrial bycatch), along with time-invariant natural mortality and proportion mature values, were taken from the relevant ICES assessment working group reports (ICES 2006b, ICES 2007a). Model and management parameters were set. These included biological reference points, age ranges over which to calculate mean F, the plus-group age a_{pg}, and assessment model settings. Assessment data for total catch numbers $C_{a,y}$ and yield Y_y were derived from data on landings and discards.

An initial FLXSA stock assessment (Shepherd 1992, Darby and Flatman 1994, Kell 2011) was run, using data up to and including year $\gamma - 1$ (which was 2006 in this case study). This assessment generated estimates of abundance $\hat{N}_{a,y}$, recruitment $\hat{R}_y = \hat{N}_{0,y}$ (age 0 is the first age in the North Sea haddock dataset), and fishing mortality $\hat{F}_{a,y}$, and enabled subsequent estimation of the following:-

1. Catchability $q_{i,a}$ for each survey. This was assumed to be related to estimated abundance via a power relationship, and was estimated for each survey i and age

a by minimising the sum-of-squares

$$\mathrm{SSQ}_q = \sum_{i,a,y} \left(I_{i,a,y} - \hat{q}_{i,a} \hat{N}_{a,y}^{\hat{p}_{i,a}} \right)^2, \tag{4.3}$$

where $\hat{p}_{i,a}$ is the estimated power term in the catchability relationship for each age a and survey i.

2. Parameters of simulated recruitment. These were the mean and variance of the low-to-moderate recruitments observed during 1995-1998 and 2000-2006, and the estimate of the high 1999 year-class recruitment. A key requirement for applying the model to North Sea haddock is to ensure that it encapsulates adequately the sporadic nature of recruitment for the stock. Historically, North Sea haddock recruitment has followed a pattern of occasional large year-classes (the size of which seems unrelated to parental stock size, at least directly), interspersed with years of low-to-moderate recruitment (Figure 4.5). In the model, this pattern is replicated by stipulating one large recruitment (of the order of the 1999 year-class; around 100 thousand million fish) in a random year within each 10-year simulation period. As these simulations are 20 years long, there will therefore be exactly two large year-classes within each iteration; this seems to be consistent with historical observations. A further proviso is to ensure that the large year-classes are separated by at least two years, as North Sea haddock have never been observed to produce two large year-classes in succession. This may be due to cannibalism (age-1 fish predating on age-0 juveniles from the following year-class) or other density-dependent effects (Fogarty et al. 2001). Recruitment for the remaining years in the simulation is given by a lognormal distribution about the geometric mean (around 10 thousand million fish) of the ten years prior to 2006, not including 1999.

3. Selection ζ_a. This is a measure of how fishing mortality F varies with age a, and was given for each age by the mean of the last three historical F estimates. If γ was the first assessment year ($\gamma = 2007$ in the case study), then:

$$\zeta_a = \frac{1}{3} \left(\hat{F}_{a,\gamma-3} + \hat{F}_{a,\gamma-2} + \hat{F}_{a,\gamma-1} \right). \tag{4.4}$$

This was then rescaled so that $\sum_a \zeta_a = 1$. Selection ζ_a must be assumed to be known throughout the simulation period: if this were not the case, there would be no unique solution to the estimation of F that results in the required catch. In this case study ζ_a was assumed to be fixed throughout the simulation period, although more complicated models of time-varying ζ_a would be possible.

4. The proportions of the total catch numbers in each of the catch components (landings ρ_a^l and discards ρ_a^d) were fixed through the simulation period. They were based on three-year historical means, as follows:

$$\text{Landings:} \qquad \rho_a^{\mathrm{l}} = \frac{1}{3} \sum_{y=2004}^{2006} \frac{C_{a,y}^{\mathrm{l}}}{C_{a,y}^{\mathrm{l}} + C_{a,y}^{\mathrm{d}}} \tag{4.5}$$

$$\text{Discards:} \qquad \rho_a^{\mathrm{d}} = 1 - \rho_a^{\mathrm{l}} \tag{4.6}$$

More generally, it was also assumed that the fishery would remain at the same capacity, and fish in the same way as before. The modelling of discarding of haddock from the commercial North Sea fishery is very important for the effective simulation of the fishery and its management. However, this is a difficult issue to address successfully, as discarding activity is a function not only of stock abundance, but also of prices, costs, quota constraints, gear regulations, fishing distribution, and the availability of other fishing opportunities (amongst other factors). There was no attempt here to model discards in this way (because appropriate models do not yet exist), and fixed proportions of discarding at each age were used throughout the simulations (see Figure 4.6). As stipulated in Equations 4.5 and 4.6, the proportion discarded at age a in the simulations is the mean of the proportions discarded at age a for the years $\gamma - 3$ to $\gamma - 1$ (here γ denotes the first assessment year, which is 2007 for this case study). This is an approximation that has serious implications for the evaluation (see below), and that needs to be revisited during future work.

Finally, data objects were stipulated, and run settings defined. The settings used in the North Sea haddock case study were as follows:

Survey CV:	$\sigma_i = 0.2$
Catch CV:	$\sigma_c = 0.1$
Management type:	TAC-based landings regulation
HCR type:	Management plan with sliding-F rule
Limit in TAC change:	$\Delta\text{TAC} = 0.15 (\Rightarrow 15\%)$
Target F:	$F_{\text{target}} = 0.1, 0.2, 0.3, 0.4, 0.5$
Bycatch F:	$F_{\text{bycatch}} = 0.1$
Limit in F change:	$\Delta F = 0.25 (\Rightarrow 25\%)$
Biomass reference points:	$B_{\text{lim}} = 100\text{kt}, B_{\text{pa}} = 140\text{kt}$

The analysis algorithm

The North Sea haddock MSE analysis consisted of three concentric loops: the F_{target} loop, which considers different values of F_{target}; the k or iteration loop, which loops over different randomly-generated recruitments, and the inner y or year loop. The y-loop proceeds as follows:

1. If $y = \gamma + 1$, $F_{a,y}$ (the intermediate year fishing mortality) is set to the mean of the last three historical years. If $y > \gamma + 1$, this step is not required as the intermediate-year F is determined by previous applications of the specified HCR.

2. Recruitment in year y is given by

$$R_y = \begin{cases} R_y^{\text{high}} & y = y_1, y_2 \\ R_y^{\text{low}} & \text{otherwise} \end{cases} \tag{4.7}$$

   where

$$\ln R_y^{\text{low}} \sim N\left(\bar{R}^{\text{low}}, \text{CV}R_y\right), \tag{4.8}$$

$$\bar{R}^{\text{low}} = \exp\left(\frac{1}{10} \sum_{\substack{y=95...98,\\ 00...05}} \ln R_y\right) \tag{4.9}$$

   and

$$\text{CV}\left(R_y\right) = \text{sd}\left(\ln R_{95}, \ldots, \ln R_{98}, \ln R_{00}, \ldots, \ln R_{05}\right). \tag{4.10}$$

In addition

$$y_1 \sim U(2006, 2013) \tag{4.11}$$
$$y_2 \sim U(2016, 2023) \tag{4.12}$$

and

$$R^{\text{high}}_{y_1,y_2} \sim N\left(R_{99}, 0.1R_{99}\right). \tag{4.13}$$

Although the inclusion of a stochastic recruitment term has been decried as "paradoxical" by a minority of writers (e.g. Rochet and Rice 2009), it is a very widespread technique that seems intrinsically reasonable when precise estimates of recruitment are impossible to achieve. In addition, there has as yet been no quantitative demonstration that alternatives (such as expert judgement or comparative approaches) produce results that are any more reliable. For these reasons, I use this stochastic approach here.

3. Biological parameters are assumed to be constant throughout the simulation, so that for any a and y:

$$\text{Catch weights} \quad : \quad W^{\text{c}}_{a,y} = W^{\text{c}}_{a,y-1} \tag{4.14}$$
$$\text{Landings weights} \quad : \quad W^{\text{l}}_{a,y} = W^{\text{l}}_{a,y-1} \tag{4.15}$$
$$\text{Discard weights} \quad : \quad W^{\text{d}}_{a,y} = W^{\text{d}}_{a,y-1} \tag{4.16}$$
$$\text{Stock weights} \quad : \quad W^{\text{s}}_{a,y} = W^{\text{s}}_{a,y-1} \tag{4.17}$$
$$\text{Natural mortality} \quad : \quad M_{a,y} = M_{a,y-1} \tag{4.18}$$
$$\text{Maturity} \quad : \quad \text{Mat}_{a,y} = \text{Mat}_{a,y-1} \tag{4.19}$$
$$\text{Prop. F before spawning} \quad : \quad \text{PF}_{a,y} = \text{PF}_{a,y-1} \tag{4.20}$$
$$\text{Prop. M before spawning} \quad : \quad \text{PM}_{a,y} = \text{PM}_{a,y-1} \tag{4.21}$$

4. Abundance in year y for all $a < a_{\text{pg}}$ is given by

$$N_{a,y} = N_{a-1,y-1} \exp\left(-F_{a-1,y-1} - M_{a-1,y-1}\right), \tag{4.22}$$

and for $a = a_{\text{pg}}$, where a_{pg} is the plus-group age (in this case, a_{pg} contains all the fish aged 8 or older):

$$\begin{aligned} N_{a,y} &= N_{a-1,y-1} \exp\left(-F_{a-1,y-1} - M_{a-1,y-1}\right) \\ &\quad + N_{a,y-1} \exp\left(-F_{a,y-1} - M_{a,y-1}\right). \end{aligned} \tag{4.23}$$

5. Catch, landings and discard numbers C (as well as associated yields Y) in year y are now calculated, using

$$
\begin{aligned}
C^{\mathrm{c}}_{a,y} &= \frac{\tilde{F}_{a,y} N_{a,y} \left(1 - \exp\left(-\tilde{F}_{a,y} - M_{a,y}\right)\right)}{\tilde{F}_{a,y} + M_{a,y}} && (4.24)\\
C^{\mathrm{l}}_{a,y} &= \rho^{\mathrm{l}}_{a} C^{\mathrm{c}}_{a,y} && (4.25)\\
C^{\mathrm{d}}_{a,y} &= \rho^{\mathrm{d}}_{a} C^{\mathrm{c}}_{a,y} && (4.26)\\
Y^{\mathrm{c}}_{y} &= \sum_a C^{\mathrm{c}}_{a,y} W^{\mathrm{c}}_{a,y} && (4.27)\\
Y^{\mathrm{l}}_{y} &= \sum_a C^{\mathrm{l}}_{a,y} W^{\mathrm{l}}_{a,y} && (4.28)\\
Y^{\mathrm{d}}_{y} &= \sum_a C^{\mathrm{d}}_{a,y} W^{\mathrm{d}}_{a,y} && (4.29)
\end{aligned}
$$

   Note that $\tilde{F}_{a,y}$ here is the *intended* fishing mortality produced by a previous management decision. Under catch-based management, Equation 4.24 cannot be used directly because it is intended landings yield $\tilde{Y}^{\mathrm{l}}_{y}$ that is determined by a previous management decision, not fishing mortality $\tilde{F}_{a,y}$. In this case, a multiplier λ_y must be determined such that the application of $F_{a,y} = \lambda_y \zeta_a$ results in $N_{a,y} > 0 \; \forall \; a$ and $Y^{\mathrm{l}}_{y} \leq \tilde{Y}^{\mathrm{l}}_{y}$. Recall that ζ_a is the selection at age a from Equation 4.4. Here I am modelling a fishery which will take the predetermined TAC if possible, but not if doing so would result in negative abundance at any age. λ_y is estimated by minimising the sum-of-squares between intended yield $\tilde{Y}^{\mathrm{l}}_{y}$ and actual yield Y^{l}_{y}, constrained so that $N_{a,y} > 0 \; \forall \; a$. Once this is done, fishing mortality is given by $F_{a,y} = \lambda_y \zeta_a$ and catch by Equation 4.24.

6. Survey indices are now generated for year y: note that these are not actually used in the assessment until the following year, but it is convenient to generate them at this point in the cycle. Given catchability $q_{i,a}$, abundance $N_{a,y}$ and a random term $\varepsilon^{i}_{a,y} \sim \mathrm{N}\left(0, \sigma^2_i\right)$, survey indices are given by

$$
I_{i,a,y} = q_{i,a} N_{a,y}^{p_{i,a}} \exp\left(\varepsilon^{i}_{a,y}\right). \tag{4.30}
$$

7. Catch, landings and discards data for assessments are produced by applying random noise to true values. Given an assumed measurement error variance on catch data of σ^2_{c}, assessment catch data is given by

$$
\hat{\mathbf{C}}^{\mathrm{c}} = \left[\hat{C}^{\mathrm{c}}_{a,y}\right] = \left[C^{\mathrm{c}}_{a,y} \exp\left(\varepsilon^{\mathrm{c}}_{a,y}\right)\right], \tag{4.31}
$$

where $\varepsilon^{\mathrm{c}}_{a,y} \sim \mathrm{N}\left(0, \sigma^2_{\mathrm{c}}\right)$. Assessment landings and discards data are generated in an analogous manner to true landings and discards data:

$$\hat{\mathbf{C}}^{\mathrm{l}} = \left[\hat{C}^{\mathrm{l}}_{a,y}\right] = \left[\rho^{\mathrm{l}}_a \hat{C}^{\mathrm{c}}_{a,y}\right] \tag{4.32}$$

$$\hat{\mathbf{C}}^{\mathrm{d}} = \left[\hat{C}^{\mathrm{d}}_{a,y}\right] = \left[\rho^{\mathrm{d}}_a \hat{C}^{\mathrm{c}}_{a,y}\right] \tag{4.33}$$

where ρ^{l}_a and ρ^{d}_a are given by Equations 4.5 and 4.6 respectively. Measured yields $\hat{\mathbf{Y}}^{\mathrm{c}}$, $\hat{\mathbf{Y}}^{\mathrm{l}}$ and $\hat{\mathbf{Y}}^{\mathrm{d}}$ are calculated in a similar way to that given in Equations 4.27 to 4.29.

8. An assessment is carried out, using data (up to and including year $y-1$) for $\hat{\mathbf{C}}^{\mathrm{c}}$, $\hat{\mathbf{Y}}^{\mathrm{c}}$, $\mathbf{W}^{\mathrm{c}}$, $\mathbf{W}^{\mathrm{s}}$, $\mathbf{M}$, $\mathbf{Mat}$, $\mathbf{PF}$, $\mathbf{PM}$, and $\mathbf{I}$ (see Equations 4.14 to 4.21). The FLXSA function of FLR is used for this purpose, and returns assessment estimates of abundance $\hat{\mathbf{N}}$ and fishing mortality $\hat{\mathbf{F}}$. In the first year loop only ($y = \gamma = 2007$) these estimates are treated as the true values, so that:

$$N_{a,j} = \hat{N}_{a,j} \tag{4.34}$$

$$F_{a,j} = \hat{F}_{a,j} \tag{4.35}$$

   for $j \leq \gamma - 1$.

9. At this point I apply the sliding-F management rule. An F-multiplier is estimated that results in $F_{y+1} = F_{\mathrm{target}}$ when applied to $\hat{F}_{y-1}$. A short-term (three-year) forecast is carried out on the basis of this value of fishing mortality, using year $y-1$ as the starting point, and the resultant spawning-stock biomass $\hat{B}_{y+2}$ in the year following the quota year is generated. If $\hat{B}_{y+2} < B_{\mathrm{pa}}$, the sliding-$F$ rule is applied to generate a new F_{target} and the forecast procedure is repeated to produce a new $\hat{B}_{y+2}$. This may imply a different F_{target}, in which case the procedure is repeated until the difference between subsequent values of F_{target} is less than a pre-specified iteration tolerance. This iteration nearly always converges: if $\hat{B}_{y+2}$ flips between a value above B_{pa} and a value below B_{lim} (which can happen if B_{pa} and B_{lim} are close together), then the average of F_{target} and F_{bycatch} is used.

   If the final $\hat{B}_{y+2} > B_{\mathrm{pa}}$, the TAC constraint is applied ($\Delta\mathrm{TAC} = 15\%$, in this case). The implied intended landings yield $\tilde{Y}^{\mathrm{l}}_{y+1}$ is compared with $\tilde{Y}^{\mathrm{l}}_{y} \pm \Delta\mathrm{TAC}$. If $\tilde{Y}^{\mathrm{l}}_{y+1}$ is within this range, then the intended yield is set to that which is implied by $\tilde{F}_{y+1} = \hat{F}_{y-1} \times F^{\mathrm{m}}$. On the other hand, if the implied yield $\tilde{Y}^{\mathrm{l}}_{y+1}$ from the original forecast is *not* within the bounds specified by $\Delta\mathrm{TAC}$, then $\tilde{Y}^{\mathrm{l}}_{y+1}$ is set to

$\tilde{Y}^{l}_{y} \pm \Delta\mathrm{TAC}$ as required.

A series of low recruitments can lead to an exponential (and irreversible) increase in F as our virtual managers try to ensure that the full TAC is taken. To prevent this, a limit ΔF is stipulated on interannual change in F. If $F^{\mathrm{m}} > 1.0 + \Delta F$ then F^{m} is set to $1.0 + \Delta F$: similarly, if $F^{\mathrm{m}} < 1.0 - \Delta F$ then F^{m} is set to $1.0 - \Delta F$. It is also useful to record intended yield, which in this case is the yield implied by the modified F^{m}.

Although the process is quite complicated, the output from the evaluation is simple: the intended landings yield $\tilde{Y}^{l}_{y+1}$.

10. With management decisions now determined, the y-loop carries on to the start of the next year. The quota year from the previous y-iteration now becomes the intermediate year, and effect of fishing on the stock is now largely determined by the intended yields.

11. Once the y-loop is completed, the simulation begins again with the next k-loop and a different time-series of recruitments, and subsequently the next F_{target}-loop.

Banking and borrowing

The version of the haddock MSE produced for Needle (2008b) incorporated interannual quota flexibility (banking and borrowing). This extends the previous haddock MSE work (Needle 2008c) and increases its complexity. The key features are as follows (y is the assessment year, $y+1$ is the quota year):

1. Flexibility is only available if $B_{y-1} > B_{\mathrm{pa}}$ and $F_{y-1} < F_{\mathrm{pa}}$.
2. The options are:
   (a) Borrow up to 10% from year $y+2$ to be fished in year $y+1$.
   (b) Bank up to 10% from year $y+1$ to be fished in year $y+2$.
   (c) Only the baseline quota (i.e. that derived from the management plan) can be banked or borrowed. Thus quota borrowed from year $y+2$ must be fished in year $y+1$ or lost. Similarly, quota banked from year $y+1$ to year $y+2$ cannot be banked again.

This is applied *after* the usual management-plan calculations. It means that there needs to be two concurrent time-series of quota; the baseline quota, which is set using the management plan, and the flexi quota, which is not.

The flexi-quota algorithm is then:

1. Carry out an assessment in year y, using catch and survey data up to and including year $y-1$ and (possibly) survey data from year y.

2. Apply the management plan to get TAC^p_{y+1}, the quota suggested by the plan.

3. Apply quota flexibility if precautionary limits are not exceeded. Let ρ be the required flexibility percentage (so that, for example, $\rho = 0.1 \Rightarrow 10\%$ banking), let TAC^s_y be the standard quota, and let TAC^f_y be the flexi quota. Then, if flexibility is applied, the result is:

$$\begin{aligned} (1-\rho)\mathrm{TAC}^p_{y+1} &\mapsto \mathrm{TAC}^s_{y+1} \\ \rho\mathrm{TAC}^p_{y+1} &\mapsto \mathrm{TAC}^f_{y+2} \end{aligned}$$

   In other words, if $\rho > 0$ (banking), then $\rho\%$ of the quota for year $y+1$ has been assigned to year $y+2$ instead (the formulae are reversed if $\rho < 0$, for borrowing). Finally, the actual quota for year $y+1$ is calculated as

$$\begin{array}{lcc} \mathrm{TAC}_{y+1} & = \mathrm{TAC}^s_{y+1} + & \mathrm{TAC}^f_{y+1} \\ & (\text{calculated in year } y) & (\text{calculated in year } y-1) \end{array}$$

The following simple example illustrates the idea. Here I assume the flexibility option is taken every year, the TAC according to the plan is constant at 1000 kt, and $\rho = 0.1$ (so that 10% of the quota is banked every year). Then, recalling that TAC^p_y is the plan-derived quota in year y, TAC^s_y is the standard quota, TAC^f_y is the flexi quota, and $\mathrm{TAC}_y = \mathrm{TAC}^s_y + \mathrm{TAC}^f_y$ is what may actually be fished in year y:

$$\begin{array}{ccccccccc}
\rho & y & & \mathrm{TAC}^p_y & & \mathrm{TAC}^s_y & & \mathrm{TAC}^f_y & \mathrm{TAC}_y \\
0.1 & 1 & & & & & & & \\
 & & \searrow & & & & & & \\
0.1 & 2 & & 1000 & \longrightarrow & 900 & & & 900 \\
 & & \searrow & & & & \searrow & & \\
0.1 & 3 & & 1000 & \longrightarrow & 900 & & 100 & 1000 \\
 & & \searrow & & & & \searrow & & \\
0.1 & 4 & & 1000 & \longrightarrow & 900 & & 100 & 1000 \\
 & & & & & & \searrow & & \\
0.1 & 5 & & & & & & 100 &
\end{array}$$

The arrows follow the conceptual path for each calculation. Here the TAC settles down to an equilibrium steady state of 1000 kt, which is the TAC according to the plan in any case. If $\rho = -0.1$ (implying 10% borrowing each year):

ρ	y	TAC_y^p		TAC_y^s	TAC_y^f	TAC_y
-0.1	1					
-0.1	2	1000	$\longrightarrow$	1100		1100
-0.1	3	1000	$\longrightarrow$	1100	-100	1000
-0.1	4	1000	$\longrightarrow$	1100	-100	1000
-0.1	5				-100	

This also converges to the required steady state. Finally, if ρ alternates between ± 0.1, then:

ρ	y	TAC_y^p		TAC_y^s	TAC_y^f	TAC_y
0.1	1					
-0.1	2	1000	$\longrightarrow$	900		900
0.1	3	1000	$\longrightarrow$	1100	100	1200
-0.1	4	1000	$\longrightarrow$	900	-100	800
0.1	5	1000	$\longrightarrow$	1100	100	1200
-0.1	6				-100	

Here, the fishable TAC fluctuates around the plan TAC. So, on the basis of these simple examples, it would be reasonable to hypothesise that banking-and-borrowing is unlikely to affect adversely stock sustainability. The main reason for this appears to be the fact that quota transfers can only be done on the baseline plan-derived TAC: managers cannot borrow the same block of quota for two years in a row. I should note here that, at the time of writing, the banking-and-borrowing option for North Sea haddock has never been exercised in the real fishery.

4.4 Results

4.4.1 The North Sea haddock MSE

Figures 4.7 to 4.9 summarise the results of the analysis, which took around 75 hours to complete due to the large number of repeated iterations and minimisations required to simulate such aspects as the TAC constraint and the sliding-F rule in the bespoke R code written for this analysis. As discussed on page 16, the sliding-F iteration converged successfully on every occasion it was used.

Figure 4.7 summarises the model output for a single iteration for $F_{\text{target}} = 0.3$ (50 such iterations comprised the full analysis for a particular F_{target}). In this iteration, the effect of the $\pm15\%$ TAC constraint is clear in the time-series of intended landings (that is, quota or TAC; see Figure 4.7a). Following the sliding-F rule, the interannual change in TAC deviates from the $\pm15\%$ limits only for five years between 2018 and 2025 (Figure 4.7f), which correspond to years for which *assessed* biomass falls below B_{pa} (Figure 4.7c). However, in these years (and, indeed, in most years in the simulation), the true biomass was much higher, and this reveals the effect of the problem with discard modelling that was mentioned above (see page 22). As fishing mortality is maintained at a low level, biomass begins to rise; but the TAC constraint means that landings do not rise commensurately. In reality this would probably lead to increased discarding rate for younger ages, all else being equal, but that cannot happen in this model for which fixed proportions discarded at each age have been stipulated. For this reason, the catch (landings plus discards) on which the assessment is based is lower than it should be, and hence the assessed biomass is lower.

The data from the simulated survey series did not have this bias, but the assessment model used (FLXSA, an implementation of XSA) is largely driven by catch data with surveys playing a calibrative role (Darby and Flatman 1994). Extensive testing during model development showed that none of the FLXSA settings (shrinkage and so on) could ameliorate the effect. A higher F_{target} or the removal of the TAC constraint did reduce the problem: however, these were not part of the plan under evaluation. The under-estimation also has consequences for fishing mortality, which was mostly estimated to be higher than it really was. The result was a management plan which was actually more conservative than it needed to be.

TAC increases of greater than 15% are possible (Figure 4.7f). This will happen when a low assessment of spawning-stock biomass is combined with a large incoming year-class. The management plan operates on the basis of spawning-stock biomass, which remains low while the fish are young, so the constraint on interannual TAC variation does not apply. At the same time, the abundant young fish contribute to a higher quota forecast. The TAC must therefore increase by more than 15% if the management plan is to be followed. This result seems contradictory in a situation of low biomass, but is inevitable if the management plan is implemented as written.

The 50 iterations carried out with target $F_{\text{target}} = 0.3$ are summarised in Figure 4.8. The median values from these plots are the result of smoothing across different realisations of recruitments, and are therefore useful only as an *indication* of likely future events. The median outcome itself is not at all likely, given that each recruitment time series always has two large year-classes which are not directly reflected in the median. Median landings yield falls to a low level as the 1999 year-class is exhausted, before rising to a steady state of around 45 kt. Median fishing mortality is, for much of the time series, much lower than the F_{target} that the management plan should provide; this is due to a combination of the $\pm 15\%$ TAC constraint and the simple discard model mentioned above. Median biomass remains stable for four years or so, before rising swiftly and rebounding to a steady state well above B_{pa}. Finally, the median recruitment is low, but the occasional large year-classes are also evident as outliers.

As well as medians, Figure 4.8 also indicates the spread of possibilities, and on this basis I can examine the risk of occurrence of unwanted events. One such event would be biomass falling below B_{pa} or B_{lim}, which is what the management plan is attempting to avoid. I can estimate this risk by counting the number of years in a given iteration for which $B < B_{\text{pa}}$ or $B < B_{\text{lim}}$. If I denote the spawning stock biomass in year y in iteration k of a simulation using $F = F_{\text{target}}$ by $B_{y,k,F}$, allow B_{ref} to stand for B_{pa} or B_{lim} as appropriate, and use a test function $\kappa_{y,k,F}$ such that

$$\kappa_{y,k,F} = \begin{cases} 1, & B_{y,k,F} < B_{\text{ref}} \\ 0, & B_{y,k,F} \geq B_{\text{ref}} \end{cases} \tag{4.36}$$

then the required risk is given by

$$\text{Risk}_{k,F} = \sum_{y} \kappa_{y,k,F}. \tag{4.37}$$

The distributions and central tendencies of $\text{Risk}_{k,F}$ are then used to indicate the degree of risk associated with each management measure (which in this case means each value of F_{target}).

The risk estimates for each F_{target} are summarised in Figure 4.9, which considers the risk of both $B < B_{\text{pa}}$ and $B < B_{\text{lim}}$. The distributions of $\text{Risk}_{k,F}$ for both have had loess smoothers passed through them, to give an indication of the central tendency of risk. On the basis of these smoothers, the number of years for which $B < B_{\text{lim}}$ ranges from 0.26 years (which is 1.18% of the total) to 1.90 years (8.64%), while the values for $B < B_{\text{pa}}$ range from 1.73 years (7.86%) to 4.32 years (19.64%). That is, the risk of spawning biomass being below the limit reference point for the next 22 years, given the assumptions of the model, remains less than 10% for values of F_{target} as high as 0.5. The results for $F_{\text{target}} = 0.3$, the value stipulated in the management plan, are 0.46 years (2.10%) for $B < B_{\text{lim}}$ and 2.35 years (10.70%) for $B < B_{\text{pa}}$.

In any stock simulation of this kind, one of the key aspects to get right (if only approximately so) is the time-series of future recruitments. The assumption in this Section of two strong year classes over the next 20 years is a strong one. It is possible that the risk estimates described above are largely or entirely dependent on the year of occurrence of the first large year-class, the hypothesis being that the early appearance of this year-class would a necessary condition for low risk. This is tested in Figure 4.10, which shows $\text{Risk}_{k,F}$ for $F_{\text{target}} = 0.5$ (and considering the risk of $B < B_{\text{lim}}$ in particular) plotted against the year of the first large recruitment in the corresponding simulation iteration. The plot does not support the hypothesis; if anything, the relationship between risk and the year of the first large recruitment is slightly negative. This result suggests that the simulations are not as closely dependent on the recruitment time-series as might have been expected.

Discussion and conclusions

On the basis of the available simulations, in Needle (2008c) I reached the conclusion that the EU-Norway management plan for North Sea haddock is sustainable – that is, it provides a low risk of biomass being below the limit reference point, along with stability in quotas that will benefit the fishing industry and related economies. However, there are a number of caveats that need to be borne in mind. The analysis assumed full implementation of the quota regulations, so that the landings are precisely as intended by the specified quota, neither above nor below. In reality many situations will prevent this happening: there may be misreporting of landings by species or area, or quota uptake may be less than full (as was the case in the North Sea during 2007, and indeed most years since assessments began). Fleet activity was assumed to be static, which is unlikely. The simulations also did not consider the impact of effort management or such technical measures as may be applied to the haddock fishery, nor did they incorporate multispecies considerations. Although these factors were not stipulated directly in the management plan, they do affect the fishery and will therefore have an effect on the sustainability of the plan when it is applied.

The biological assumptions in the analyses also affected perceptions of the likely impact of the management plan. The growth of haddock is assumed to be constant into the future, although it is well known that haddock growth is affected by year class size (among other things; see ICES 2007a, Baudron et al. 2011, Jaworski 2011). Recruitment of haddock was modelled as a time-series only, with no reference to parental spawning-stock size. The lack of a clear relationship between stock and recruitment would indicate that this was reasonable, but it meant that good recruitment was possible in the simulations from extremely small adult stocks and this may not be realistic.

The simulations in Needle (2008c) were limited to 50 iterations each (due to time constraints). Generally, stochastic analyses of this kind would require 500 or more iterations before reasonable conclusions could be drawn (Davison and Hinkley 1997), and the small number used here leads to potential problems. For example, the recruitment distributions in Figure 4.8 would all be similar if sufficient iterations had been run. That they are not may have introduced unwanted effects in the analysis. At the time the analysis was carried out, this problem was very hard to avoid (although see Section 6): a run of 50 iterations took around 15 hours in the extant implementation, so that 500 iterations would occupy over 6 days of computing time. There were a number of steps in the algorithm which slowed the process down, including the live assessment, the iterative estimation of a TAC to produce a required fishing mortality rate, and the sliding-F rule. However, the difficulty may not be as significant as it at first appears. The real difference between each iteration lies in the years in which the two large year-classes appear. While there are 56 possible permutations, there are only four combinations which are likely to have any real impact: the large year-classes can appear in the first or second half of 2006–2013, and first or second half of 2016–2023. That is, the large year-classes are either close together, moderately separated and early, moderately separated and late, or far apart. It may be that 50 iterations is sufficient to cover this reduced range of outcomes, particularly following the results in Figure 4.10 which suggest that the recruitment time-series may not be all that critical. The issue of the number of iterations available is addressed in Section 6. I return to the problem of discard modelling in Section 4.5.

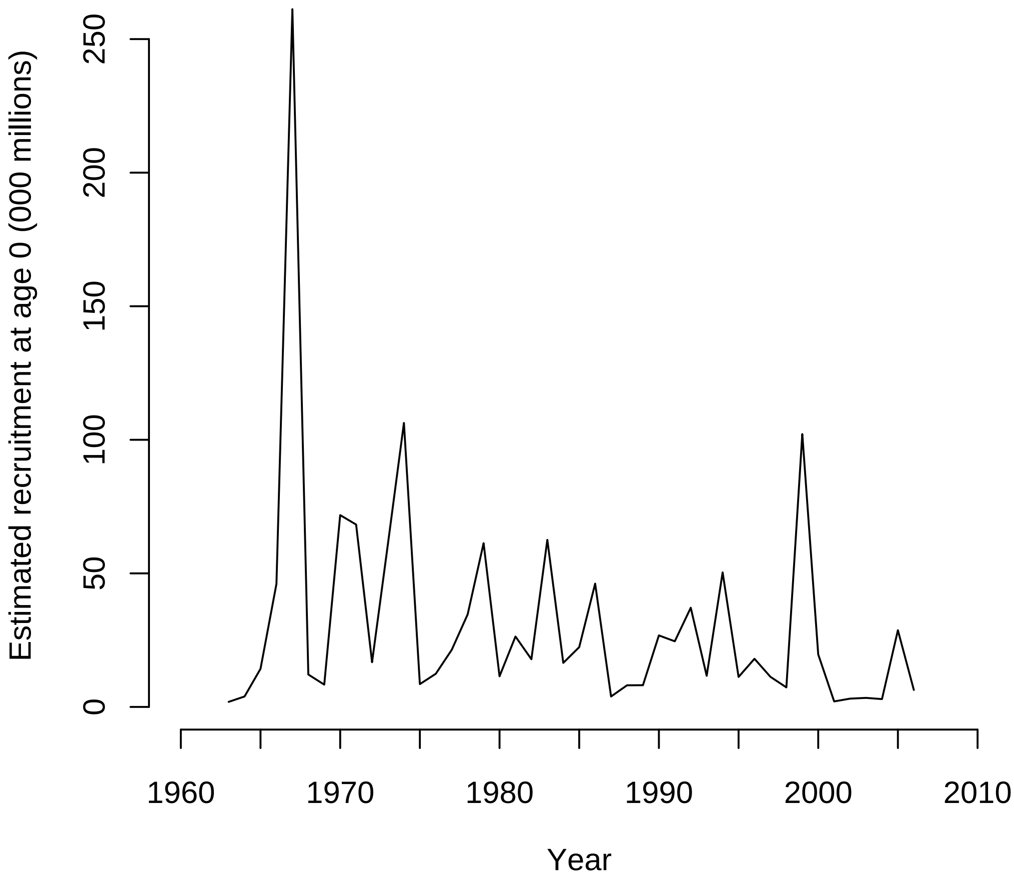


Figure 4.5: Estimated historical time-series of recruitment at age 0 for North Sea haddock.

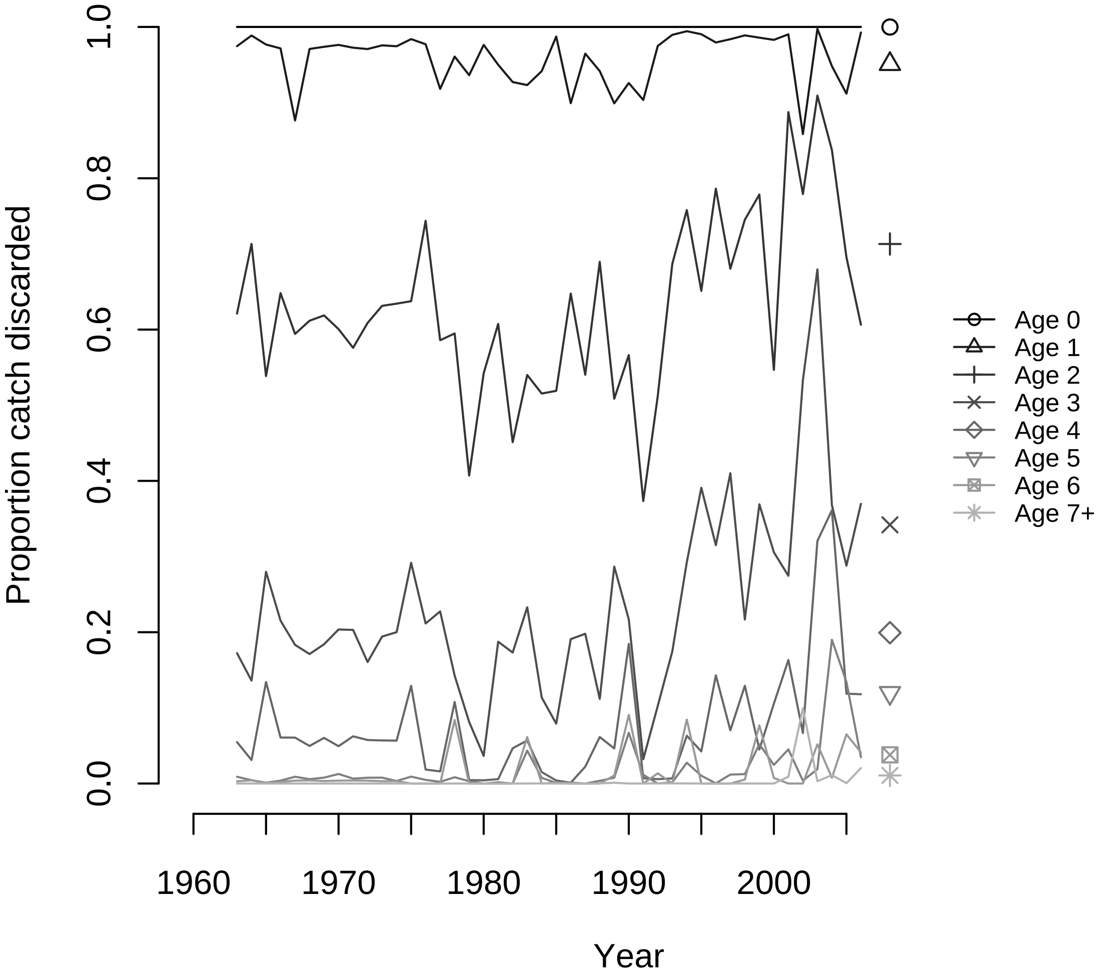


Figure 4.6: Estimated historical time-series of discards at ages 0–7+ for North Sea haddock. The lines give the proportion of total catch for each age that was discarded. The points to the far right show the three-year average discard proportions for each age that were taken forward into simulations.

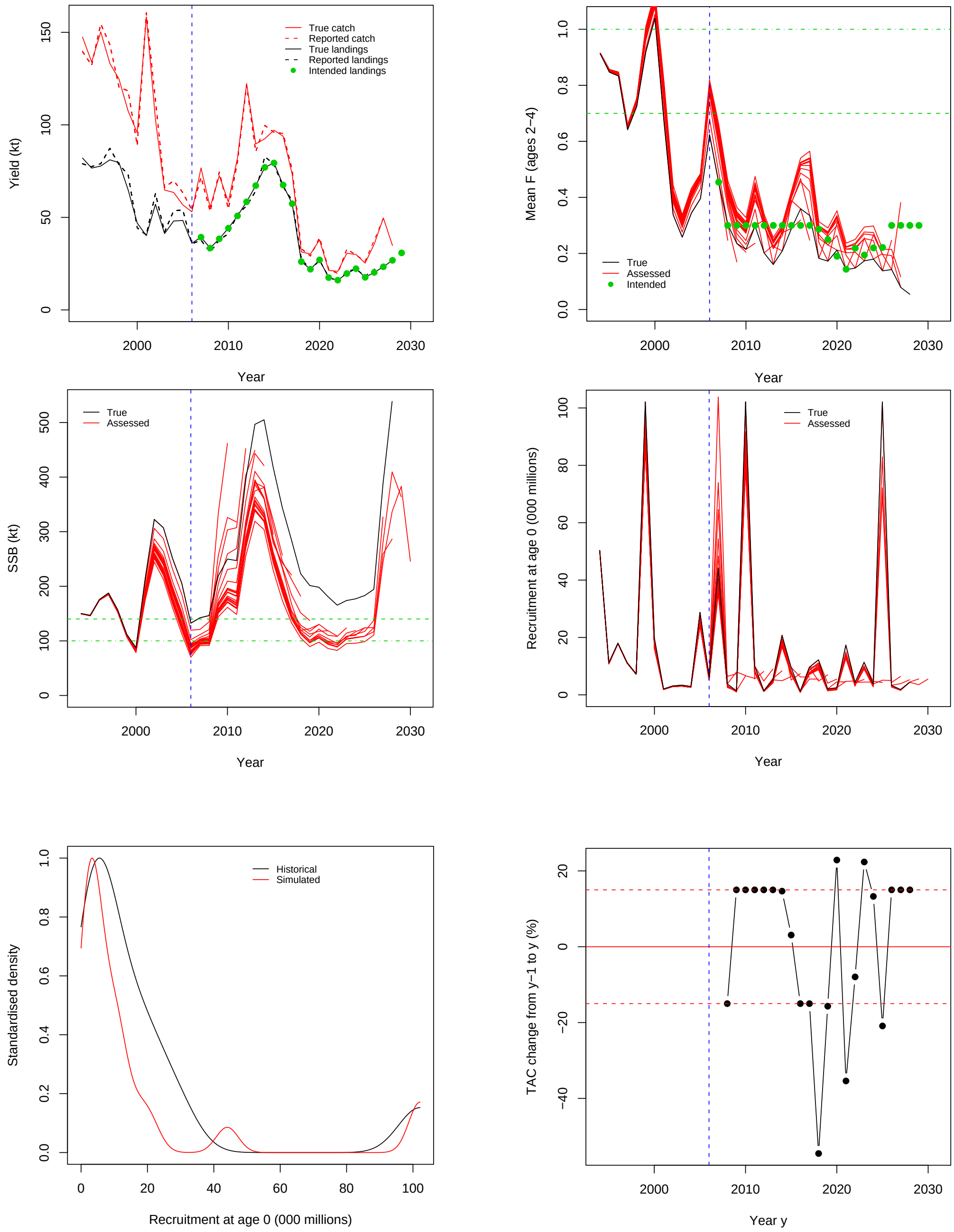


Figure 4.7: Summary plots of a single simulation iteration for North Sea haddock, with $F_{\text{target}} = 0.3$. In each plot the vertical dashed blue line delineates the last historical year. Each red line inthe top four plots shows the assessment result for one year in the future simulation. a) Yield. b) True (black) and assessed (red) fishing mortality F, with dashed green lines indicating F_{lim} (upper) and F_{pa} (lower). c) True (black) and assessed (red) spawning-stock biomass B, with dashed green lines indicating B_{pa} (upper) and B_{lim} (lower). d) True (black) and assessed (red) recruitment to the fished stock. e) Comparison of frequency distribution of historical and simulated recruitment. f) The percentage interannual change in quota (TAC), with dashed red lines showing the $\pm 15\%$ level. Source: Needle (2008c); see also Chapter VI.

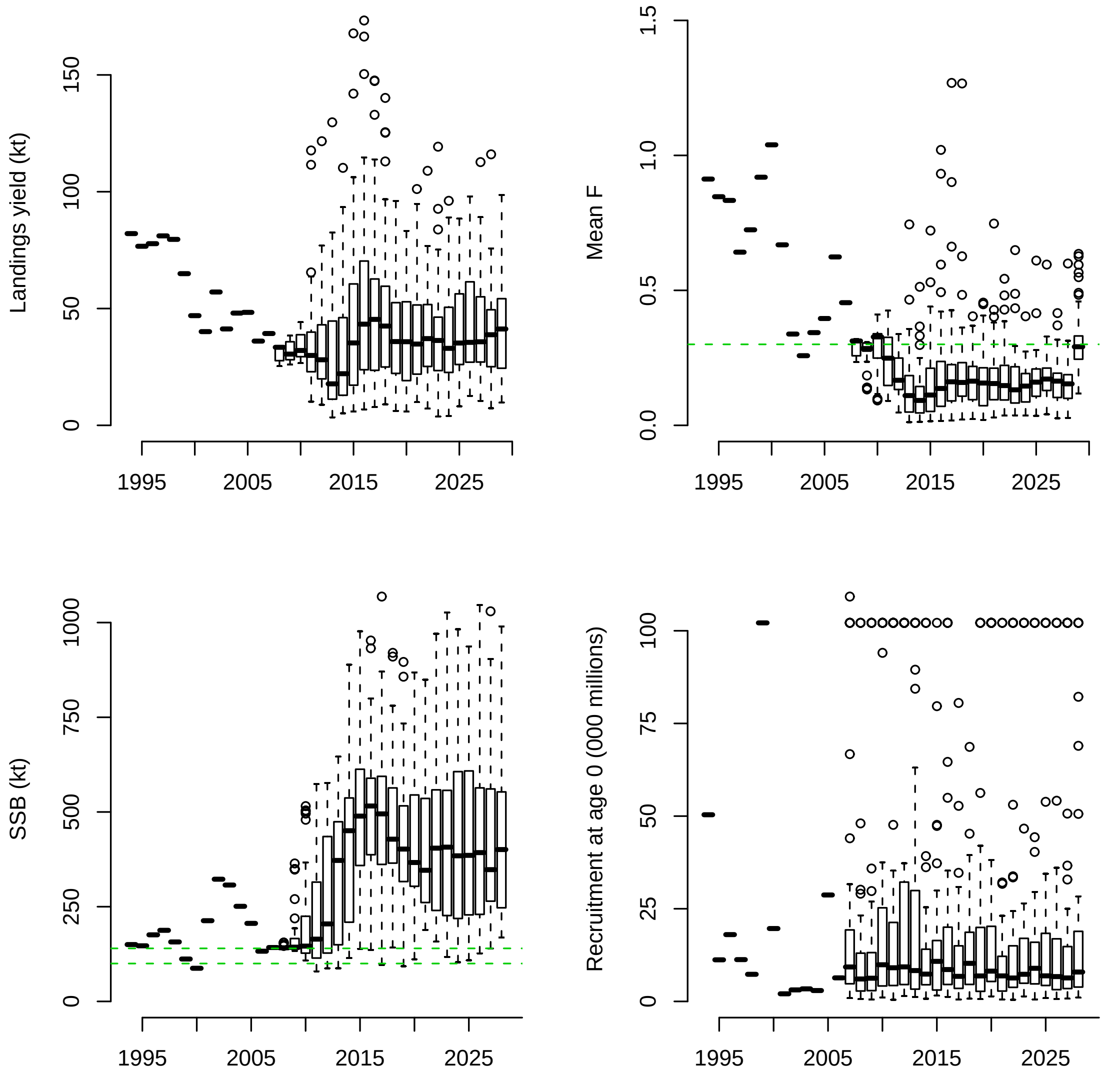


Figure 4.8: Summary plots of 50 simulation iterations, with $F_{\text{target}} = 0.3$. The short horizontal lines indicate the medians, and the boxes the quartiles (25%ile and 75%ile). The lower whisker gives the value of $25\%\text{ile} - (1.5 \times (75\%\text{ile} - 25\%\text{ile}))$ and the upper gives $75\%\text{ile} + (1.5 \times (75\%\text{ile} - 25\%\text{ile}))$. Outliers beyond this range are shown by open circles. The dashed green line on the top-right plot shows F_{target}, while those on the bottom-left plot show B_{pa} (upper) and B_{lim} (lower). Historical estimates (pre-2007) are shown as short horizontal lines only. Source: Needle (2008c); see also Chapter VI.

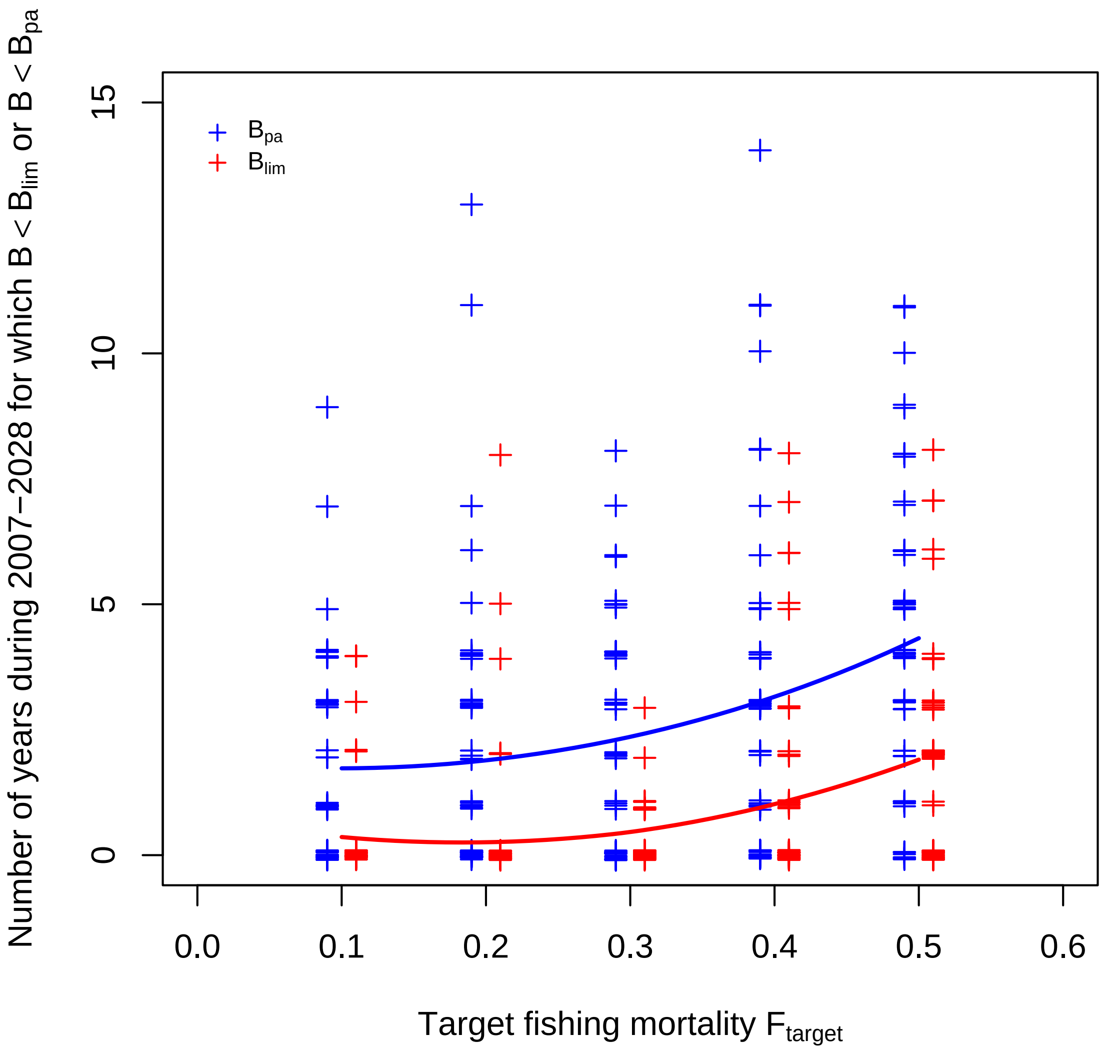


Figure 4.9: Summary of risk of $B < B_{\mathrm{pa}}$ (blue) and $B < B_{\mathrm{lim}}$ (red) for different values of F_{target} (over 50 iterations for each value). The correspondingly-coloured solid lines show the fits of loess smoothers to the full time-series of risk estimates. Small random perturbations have been applied to the vertical position of each cross to improve visualisation. Risk is defined as the number of years in each simulation for which spawning stock biomass $B < B_{\mathrm{pa}}$ or $B < B_{\mathrm{lim}}$ as appropriate. Source: Needle (2008c); see also Chapter VI.

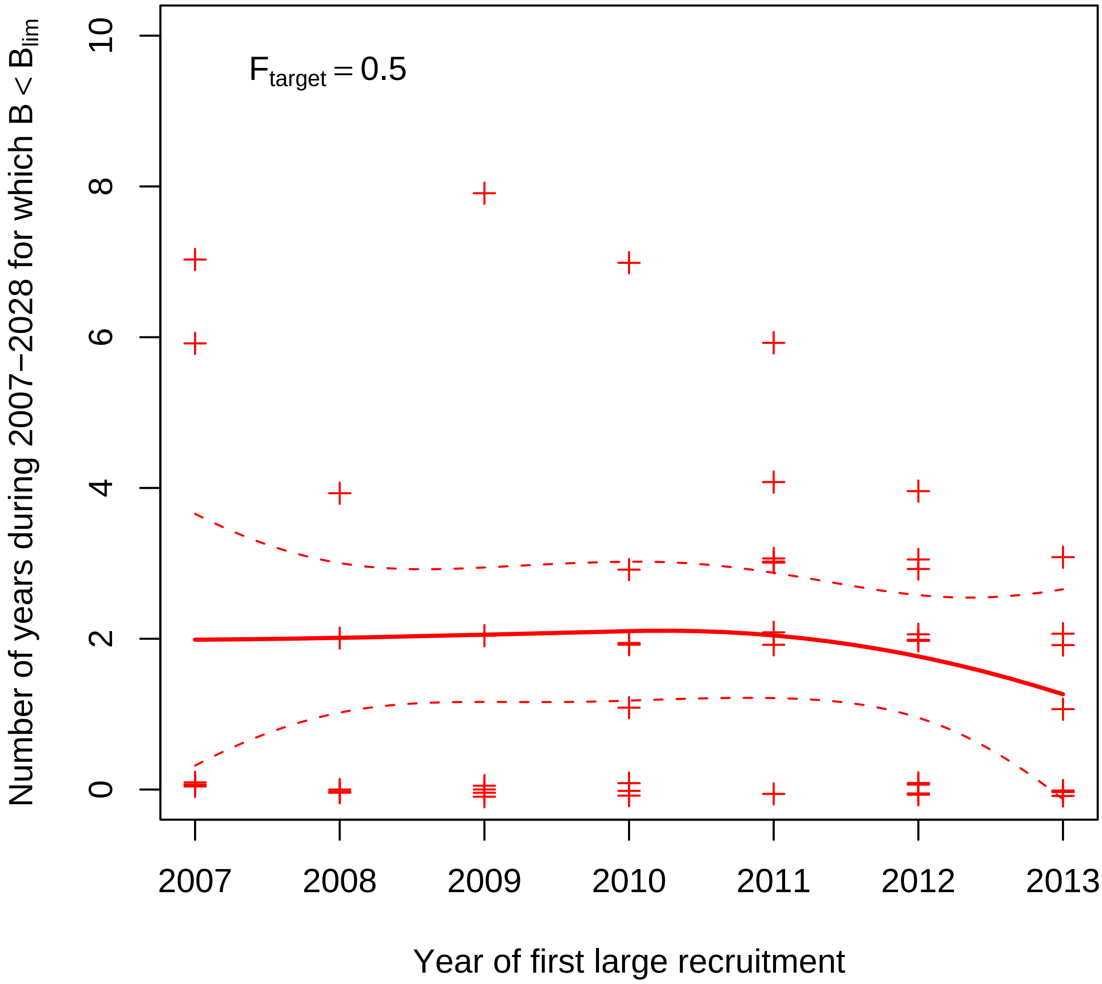


Figure 4.10: The relationship between risk and the simulation year in which the first large recruitment event occurs. Risk is defined here as the number of years in each simulation for which spawning stock biomass $B < B_{\mathrm{lim}}$. Each cross gives the result for one of the 50 simulations performed, in this case with $F_{\mathrm{target}} = 0.5$, and small random perturbations have been applied to the vertical position of each cross to improve visualisation. The solid line shows a loess smoother passed through the data, while the dotted lines give ± 2 standard errors of the smoother. Source: Needle (2008c); see also Chapter VI.

4.4.2 Extension to include banking and borrowing

The distributions of yield, mean F, SSB and recruitment over the 100 iterations carried out for each simulation including banking and borrowing are given in Figures 4.11 (for run 1) and 4.12 (for run 5): the plots were almost identical for runs 1–4 (with two strong year-classes in each run), and for runs 5–8 (with no strong year-classes), so only two plots need be shown here. The only difference between the runs in each set is the sequence of banking and/or borrowing (see page 27), so these Figures imply that the application of interannual quota flexibility makes very little difference to the future dynamics of the stock and the fishery. The key issue of inappropriate modelling of discards, and the consequent impact on management perceptions within the simulations, could not be addressed in this revised analysis (see Section 4.5).

An appropriate index of risk for the management plans analysed here is the number of years in each simulation in which biomass is less than B_{pa} or B_{lim}. This is summarised for the eight extant runs in Figure 4.13. A slightly different way of looking at risk is given in Table 4.1, which gives the percentage of iterations for each year for which biomass is less than B_{pa} or B_{lim}, averaged over all the years of the simulations. Risk is clearly higher for the runs with lower recruitment (around 15% of years with $B < B_{\mathrm{pa}}$ and 3% with $B < B_{\mathrm{lim}}$) than for runs with two strong year-classes (around 10% of years with $B < B_{\mathrm{pa}}$ and 1% with $B < B_{\mathrm{lim}}$). What constitutes a satisfactory level of risk is something for managers to determine as part of a consultation process. The important point to note here is that the risk is very insensitive to the particular sequence of banking or borrowing that is carried out.

Run	$B < B_{\mathrm{pa}}$	$B < B_{\mathrm{lim}}$	Recruitment	Quota flexibility
1	9.63	0.91	Two strong year-classes	No banking or borrowing
2	9.45	0.91	Two strong year-classes	10% banking every year
3	9.91	0.91	Two strong year-classes	10% borrowing every year
4	10.00	1.00	Two strong year-classes	Alternating 10% banking and borrowing
5	15.18	2.72	No strong year-classes	No banking or borrowing
6	15.00	2.55	No strong year-classes	10% banking every year
7	15.45	2.72	No strong year-classes	10% borrowing every year
8	14.73	2.55	No strong year-classes	Alternating 10% banking and borrowing

Table 4.1: North Sea haddock with possible banking-and-borrowing: risk of biomass B being below the specified reference points. Numbers give the percentage of iterations in each year in the forward simulations for which biomass was lower the relevant point, averaged over 25 years carried out for each run.

The banking-and-borrowing simulations described here were based on the earlier work on the North Sea haddock MSE presented above. The problem of modelling discard behaviour that was present in the earlier work was not rectified in the banking-and-borrowing analyses, so results must be considered with that caveat in mind. Given this and the other simplifying assumptions made, the conclusion must be that the sequences of banking-and-borrowing implemented do not make any significant difference to the future dynamics of the stock and the fishery. As these trial runs included the most extreme types of interannual quota flexibility permitted by the proposed regulation, it is very unlikely that any actual sequence of banking-and-borrowing would have any deleterious effect on future stock sustainability.

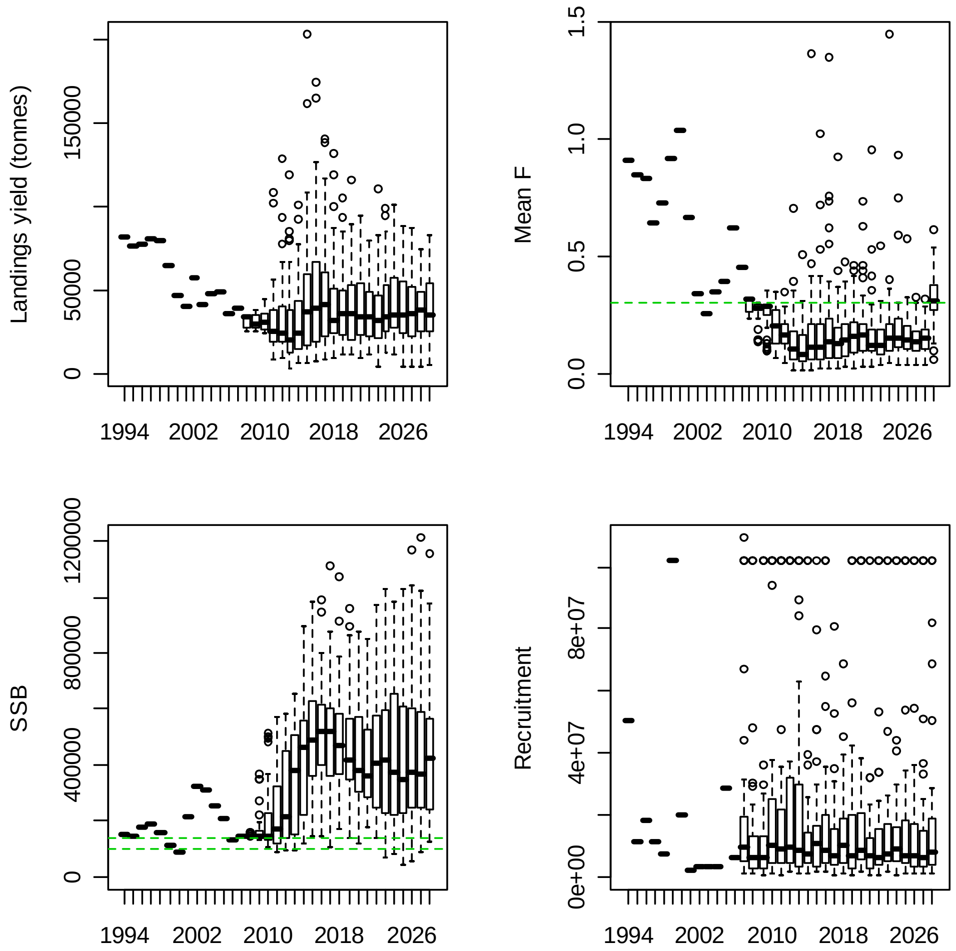


Figure 4.11: North Sea haddock with possible banking-and-borrowing: distributions of landings, SSB, mean F and recruitment from run 1 (two strong year-classes, no banking or borrowing). The short horizontal lines indicate the medians, and the boxes the quartiles (25%ile and 75%ile). The lower whisker gives the value of 25%ile $-$ (1.5 $\times$ (75%ile $-$ 25%ile)) and the upper gives 75%ile $+$ (1.5 $\times$ (75%ile $-$ 25%ile)). Outliers beyond this range are shown by open circles. The green dashed line in the mean F plot gives the target-F value for the simulation, while the equivalent lines in the SSB plot give B_{lim} and B_{pa}.

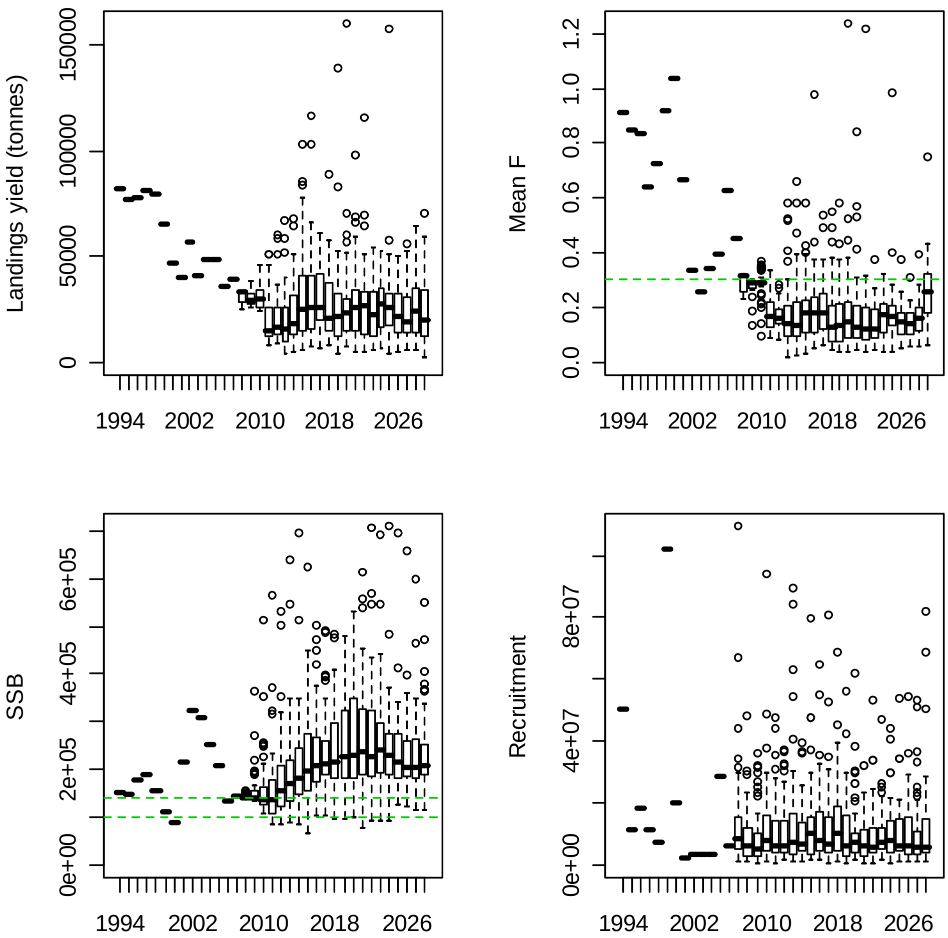


Figure 4.12: North Sea haddock with possible banking-and-borrowing: distributions of landings, SSB, mean F and recruitment from run 5 (no strong year-classes, no banking or borrowing). See caption for Figure 4.11 for plot key.

4.5 Problems with the evaluations

Regarding this thesis, the principal germane point of the North Sea haddock management evaluations carried out thus far is that the evaluations used a very simple model of future discarding practice (one aspect of fleet behaviour) which has a demonstrably deleterious effect on the outcomes. The banking-and-borrowing analysis serves to demonstrate the flexibility of the approach in simulating different types of management plan, but could not address this central issue.

Consider Figure 4.7, which summarises one simulation run from Needle (2008c). Realised mean fishing mortality in all the evaluation runs is well below the target F value of 0.3, which means that the management simulation is likely to be more conservative that it should be. This problem relates to the way in which discarding is

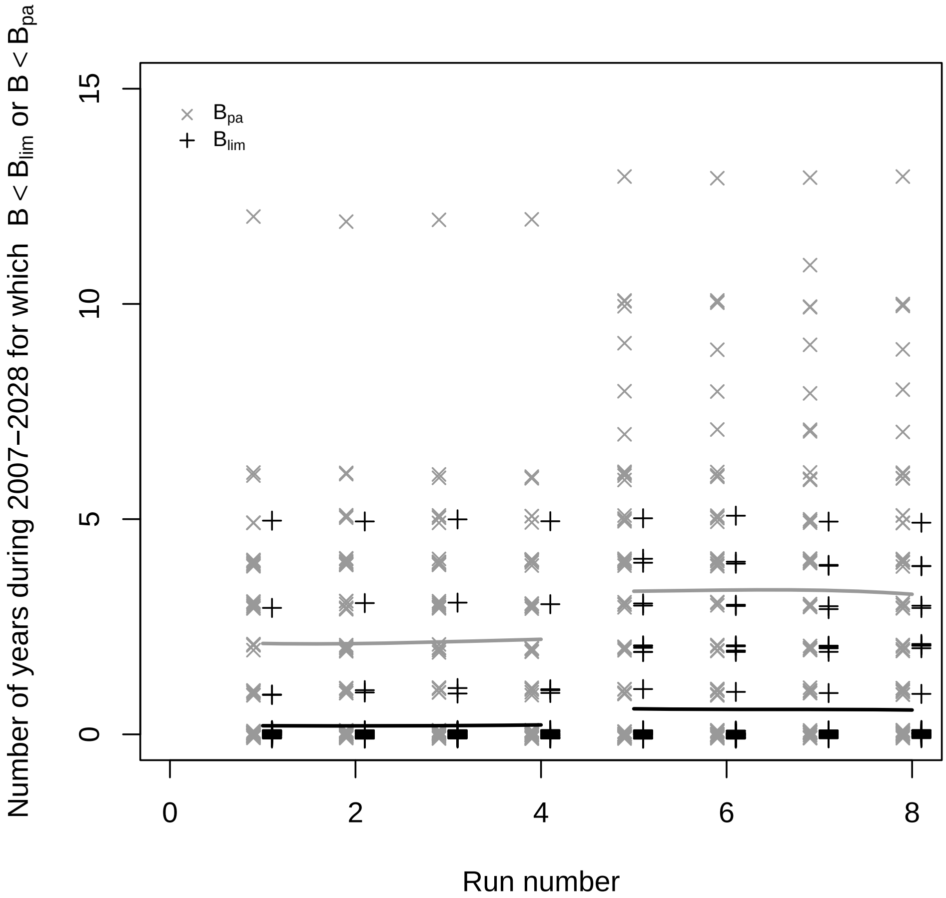


Figure 4.13: North Sea haddock with possible banking-and-borrowing: summary of risk of $B < B_{\mathrm{pa}}$ (grey) and $B < B_{\mathrm{lim}}$ (black) for different runs. The correspondingly-coloured solid lines show the fits of loess smoothers to the full time-series of risk estimates. Small random perturbations have been applied to the vertical position of each cross to improve visualisation. Risk is defined as the number of years in each simulation for which spawning stock biomass $B < B_{\mathrm{pa}}$ or $B < B_{\mathrm{lim}}$ as appropriate.

modelled in the simulations. There does not yet exist a model that can explain the discarding behaviour of North Sea fishing fleets, and I had therefore to use the crude approximation that the proportions discarded-at-age at the end of the historical time-series (actually, the mean proportions over 2005–2007) are carried forward unchanged into the future simulations. In reality, discarding proportions will change over time for many different reasons, and in particular may increase when a large year-class appears. One reason for this is the TAC cannot increase commensurately with stock biomass, because the quota is constrained to change by no more than $\pm 15\%$ each year. The consequence of this feature (in a situation of increasing biomass) is that the assessment process within the management cycle thinks that the catch is less than it actually should be. Because of this, the assessment estimate of biomass is smaller than the real biomass, and the estimate of fishing mortality is correspondingly higher than the real fishing mortality. Therefore, while the "managers" in the simulations think that mean F is around the target value of 0.3, the real mean F is consistently lower. However, a large year-class is not the only driver of discarding practices, and there are many others (such as market prices and quota availability) which are external to the stock and thus more difficult to build into these evaluations.

Previous authors have noted the deleterious effect that a discrepancy between predicted mortality and realised mortality can have on the sustainability of a management plan: an example is Holt and Peterman's (2006) study of management plans for Fraser River sockeye salmon in British Columbia. If predicted mortality is higher than realised, as was often the case in the North Sea haddock simulations presented in this Section, the danger is of lost yield and unnecessarily disadvantaged fishing communities. If realised mortality is higher than predicted, as with the case discussed by Holt and Peterman (2006), it is likely that the management plan will be much less sustainable than expected.

Solving problems of this kind calls for more extensive and realistic models of fishermen's decision-making than currently exist. This issue is one of the main motivating drivers for this thesis. Without a better knowledge of why fishermen act as they do, and what their likely reaction to changes in management and population dynamics will be, management strategy evaluations are much less useful or reliable than they could be. Past evaluations have not often included this aspect: case studies like Eggers (1992) and Holt and Peterman (2006) have generally considered correlations between potential driving forces and outcomes, rather than true process models through which causation can be determined.

5 Management strategy evaluation for West of Scotland haddock

5.1 Introduction

This Section is based on analyses first presented in Needle (2010a). I include it here as it builds on the North Sea haddock case study (see Section 4) and introduces a new issue which a general fisheries simulation model needs to be able to address: how to simulate survey-based management in which not just discards, but also unallocated removals need to be modelled.

The North-Western Waters Regional Advisory Council (NWWRAC) is a focus and lobbying group, consisting of stakeholders in the fisheries in the areas to the north and west of the UK. These stakeholders include representatives of the relevant fishing industries, non-governmental environmental groups, and fisheries managers. Scientists are not generally members of the NWWRAC (or other RACs), but they may be invited to provide advice and analyses when required. The main purpose of the European RACs (of which there are seven at the time of writing) is to provide stakeholders with a voice and input to the European advisory and management process which they may previously have been lacking.

The NWWRAC Focus Group on Management for West of Scotland haddock met at the Marine Laboratory, Aberdeen, on 3 July 2009 to discuss options for management approaches for the haddock stock in ICES Division VIa (see Figure 4.1). In particular, they considered a draft request for advice that had been made to ICES from the European Commission (EC), which called for an evaluation of the utility of applying the EU-Norway long-term management plan for North Sea haddock to Division VIa haddock (see Figure 4.1), given appropriate changes in specified biomass reference points. The key aspects of this plan, as described in Section 4 above, are a target fishing mortality (F) derived through a sliding-F rule based on forecast biomass, and a constraint on interannual change in quota.

The Focus Group concluded that the terms of the EC request to ICES formed an appropriate basis for consideration for haddock management in Division VIa, with the following provisos:

1. Target fishing mortality rates for the sliding-F rule and the TAC constraints would need to be specified appropriately for the stock. This could only be done following evaluation over the following ranges: target F from 0.2 to 0.4, and TAC constraints from $\pm15\%$ to $\pm25\%$.

2. While explicit technical measures need not form part of the management plan, the Focus Group emphasised that such measures should at least be alluded to in the text of the plan (if not directly specified). Previous versions of the North Sea haddock management plan had included such clauses. Their relevance is that they ensure that the plan is not viewed in isolation from the wider management structure.

It was agreed that I would conduct the necessary management strategy evaluation (MSE), building on the experience of running similar evaluations for the functionally-identical North Sea haddock management plan (Needle 2008c, Needle 2008b, Section 4 and Chapter VI). Once the EC request had been formally received by ICES, arrangements were made for me to complete the required analyses by 18 November 2009 for subsequent ICES review.

The Focus Group outlined the following important issues to be resolved for the evaluations (in ascending order of difficulty and tractability):

1. The stock-recruitment model to be used;
2. How to implement a live assessment module in the evaluation loop, where no FLR function to replicate a Time Series Analysis (TSA) assessment exists;
3. Accounting for potential density dependence in growth;
4. Discard models (although these are also lacking from the North Sea evaluation);
5. Multispecies fleet models.

In the evaluation presented below, points 1 and 2 have been addressed in full, while the time available was not been sufficient to cover points 3 to 5. The evaluation was implemented in the R programming system (R Development Core Team 2011, version 2.8.1), using FLR libraries (FLR Team 2006, Kell et al. 2007, Hillary 2009, `http://flr-project.org/`).

5.2 SPECIFIC MODELLING ISSUES FOR WEST OF SCOTLAND HADDOCK

It was envisaged that the development time for this evaluation would be relatively brief, as it was thought that much of the North Sea evaluation code (which had taken over two years to develop) could be reused. This did prove to be the case to a certain extent, but there were also a number of issues specific to the VIa haddock evaluation that needed to be addressed. These issues are summarised below. Aside from these, all other algorithms and assumptions were carried over from the North Sea haddock example (see Section 4).

5.2.1 Recruitment

The recruitment model for the North Sea haddock evaluation was based on the assumption that there occurs one very large year-class every ten years (where "very large" means at least two orders of magnitude greater than the mean). This pattern has not been observed to the same extent for VIa haddock, for which the range of year-class strengths is narrower (Figure 5.1), so a different approach was taken.

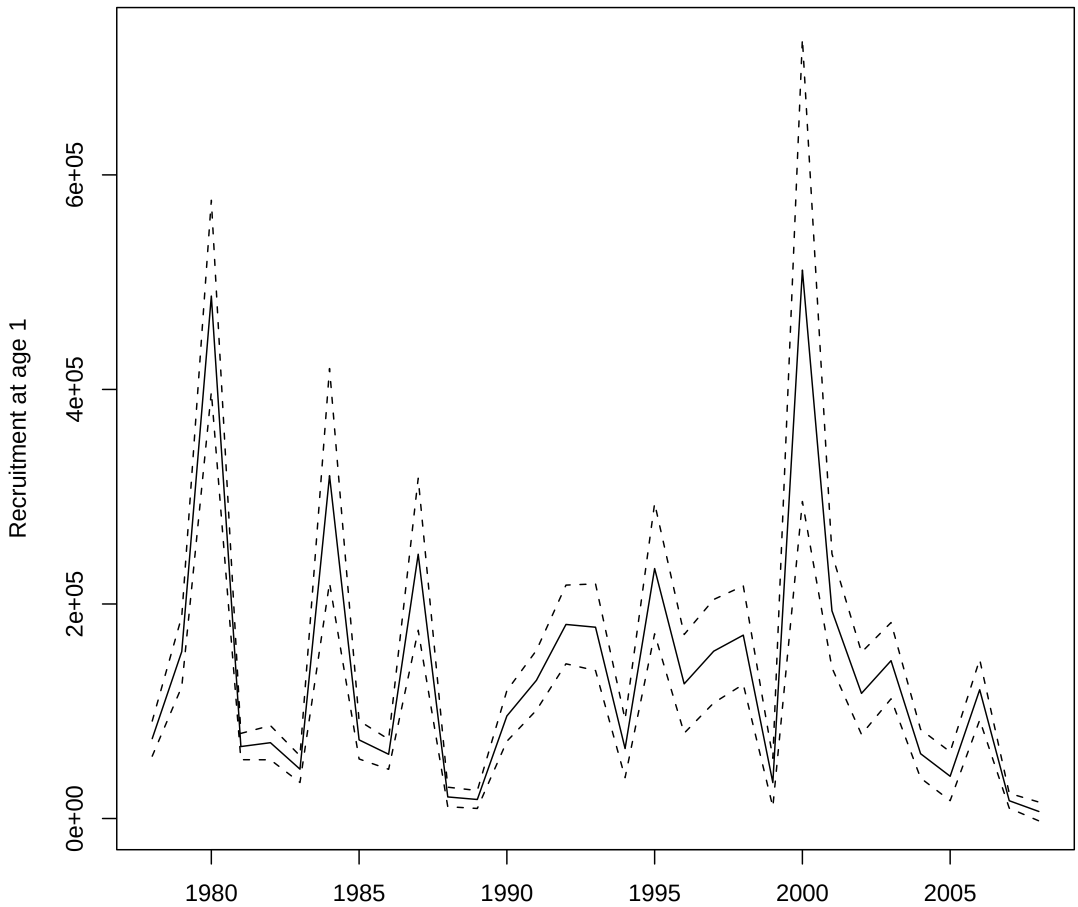


Figure 5.1: Time-series of recruitment at age 1 (in thousands) for haddock in ICES Division VIa, as estimated by ICES (2009c) using the TSA method. Dotted lines give the approximate pointwise 95% confidence intervals for the TSA estimates.

Time series of estimated parental spawning-stock biomass B and subsequent recruitment at age 1 R were taken from the most recent ICES assessment working group report (ICES 2009c). Five nested stock-recruit models were fitted to these data, using linear least-squares regression. The models used are given in Table 5.1 (see also Needle 2002).

Model	Formulation
Changepoint	$R = \begin{cases} \alpha, & S > \beta \\ \frac{\alpha S}{\beta}, & S \leq \beta \end{cases}$
Linear	$R = \alpha S$
Power	$R = \alpha S^{\beta}$
Ricker	$R = \alpha S \exp(-\beta S)$
Saila-Lorda	$R = \alpha S^{\gamma} \exp(-\beta S)$

Table 5.1: Management strategy evaluation of haddock in ICES Division VIa: recruitment model formulations. R and S are recruitment and SSB respectively; α, β and γ are parameters to be estimated.

Model fit confidence intervals were estimated using parametric sampling, as described in Needle and Hillary (2007). The goodness-of-fit of each recruitment model was tested using the AIC measure (Akaike 1973).

Following the approach suggested by Needle et al. (2003), time-series of log residuals r_t were generated for each recruitment model, where $r_t = \ln\left(R_t/\hat{R}_t\right)$: that is, the log ratio of observed to fitted recruitment for each year t. A number of ARMA(p,q) models were fitted to each time-series, for autoregressive orders $p = 0,\ldots,3$ and moving average orders $q = 0,\ldots,3$, where:

$$r_t = \phi_1 r_{t-1} + \ldots + \phi_p r_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}. \quad (5.1)$$

Here $\varepsilon_t \sim N\left(0,\sigma^2\right)$, while ϕ_p and θ_q are fitted autoregressive and moving average parameters respectively. The goodness-of-fit of the 16 resultant ARMA model fits was tested, again using the AIC measure.

The best-fitting models, as determined by this process, were used to generate recruitments in the future stock simulations as follows. The selected ARMA model was used to generate future residuals r_t, by random sampling from the distribution of ε. These residuals were then transformed back to recruitments using $R_t = \hat{R}_t e^{r_t}$, for which $\hat{R}_t$ was produced by the selected recruitment model.

Test runs showed that this approach could sometimes yield recruitments that were larger than has been observed historically for this stock. Stochastically-generated future recruitment residuals were therefore capped to lie within the range

$$\tilde{r} \in \{\min\{r_t\}, \max\{r_t\}\}. \quad (5.2)$$

5.2.2 Assessment and data streams

The Division VIa haddock assessment (ICES 2009c) is carried out using a variant of the TSA model (Fryer 2001), in which catch data for the most recent period are removed from the analysis. The assessment for recent years is therefore based largely on survey data, scaled to the level of historical catches, and recent assessments have suggested that there is a substantial component of unaccounted removals from the stock (presented as the difference between observed and estimated catches: see Figure 5.2). The removals are further divided into landings, for which official records exist, and discards, the levels of which are extrapolated from Scottish observer sampling.

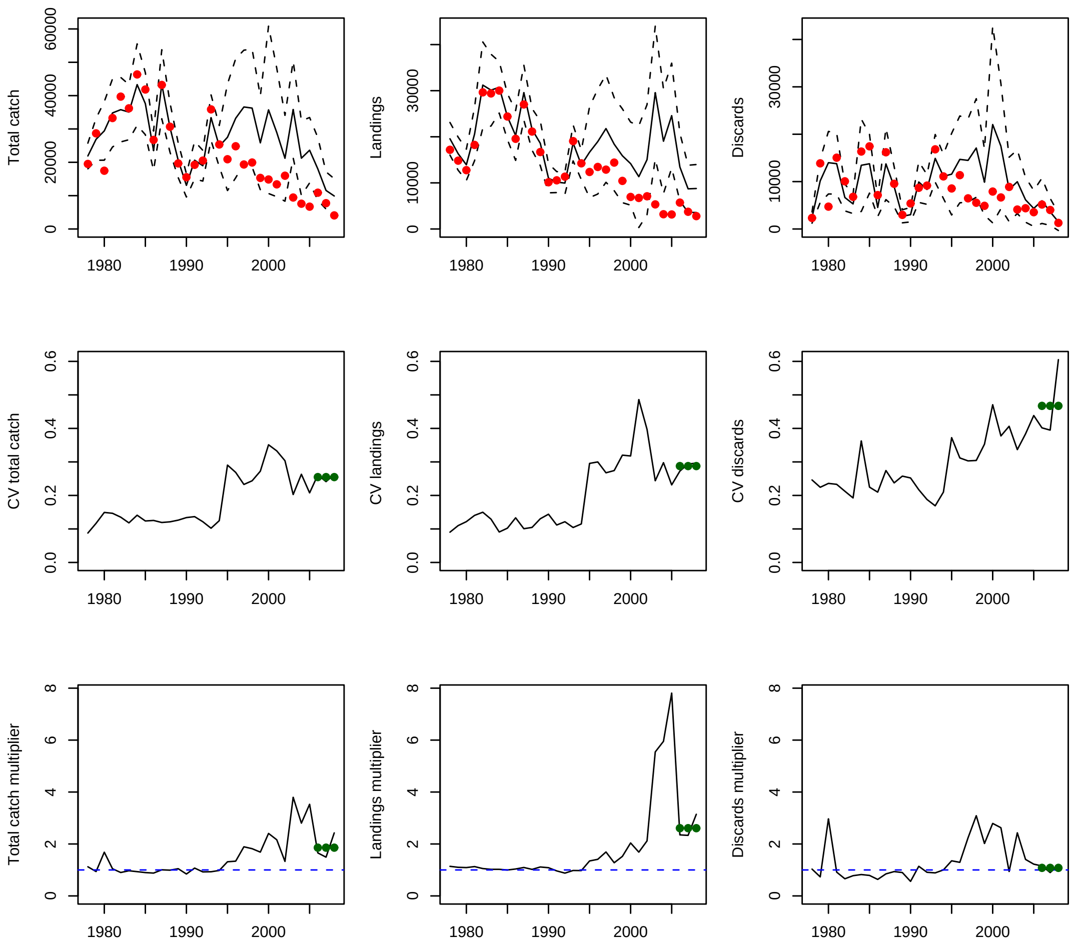


Figure 5.2: Estimated and reported catch data for haddock in ICES Division VIa, from ICES (2009c). Columns show total catch (left), landings (middle) and discards (right). Top row: yield time-series (tonnes). Red dots give reported values, lines give TSA estimates (solid) with approximate pointwise 95% confidence intervals (dashed). Middle row: TSA estimates of the coefficients of variation (CVs). Bottom row: ratio of estimated to observed values. For both middle and bottom rows, green dots show the mean of the last three values. For the bottom row, the blue lines show a ratio of 1.0 - i.e. where observed and estimated values are equal.

This structure causes problems for the MSE, over and above those encountered when evaluating the North Sea haddock management plan (see Section 4; also Chapter VI, Needle 2008c, Needle 2008b). In order to maintain as much realism in the simulations as possible, the distinction between estimated and observed catches has to be maintained moving forward in time, as does the distinction between landed and discarded catch. For North Sea haddock, this was achieved by running a biological module that generated a "true" population, followed by a knowledge-production module that generated catches (landings plus a fixed discarded proportion) and surveys, and subsequently an assessment module that used this information to run the same stock assessment model as the real Working Group to generate an "assessed" population. This assessed population was then fed into the management module to trigger management decisions for the following year.

This approach was not possible for VIa haddock, as there was no implementation of the TSA model that was accessible from the R system that I used for the evaluation. Instead, I attempted to replicate the structure in simulations as follows:

1. **Reported** landings in year y, in terms of weight landed $\left(L_y^r\right)$ and numbers-at-age landed $\left(l_{a,y}^r\right)$ are generally determined by the quota for that year, where this is set by the management module run in the previous year. If there are not enough fish available for the quota to be taken, reported landings will be adjusted downwards *pro rata*. I assume that the full quota is taken by the fleet if there are fish available to do so. Under-utilisation of quota is a common feature of several haddock fisheries, but I have not attempted to model it here. Given reported landings, reported catch $\left(C_y^r \text{ and } c_{a,y}^r\right)$ and discards $\left(D_y^r \text{ and } d_{a,y}^r\right)$ are generated using the same proportions-at-age as for true catch, landings and discards (see below).

2. **True** catch yield in year y, measured in tonnes and denoted by $\left(C_y^t\right)$, is the yield which is actually removed from the population each year by fishing. It is generated in the simulations by applying a fixed multiplier to reported catch yield. The multiplier is derived from the average of the ratio of estimated to observed catches for the last three years of historical data (see Figure 5.2, bottom row). True catches are also generated in terms of numbers of fish at each age, which I denote as $c_{a,y}^t$. From these values I further generate true landings $\left(L_y^t \text{ and } l_{a,y}^t\right)$ and discards $\left(D_y^t \text{ and } d_{a,y}^t\right)$ by applying fixed proportions-at-age: these are derived from the average of the proportions landed and discarded at age over the last three years of historical data.

3. Finally, I consider the **assessed** population, which (as in Section 4) will not necessarily be the same as the true population. As stated above, the evaluation cannot include the actual assessment used to provide advice for this stock. Instead, I have derived assessed stock numbers $N_{a,y}^{A}$ and fishing mortalities $F_{a,y}^{A}$ directly from the true stock numbers $N_{a,y}$ and fishing mortalities $F_{a,y}$ by applying random noise (with a specified but fairly *ad hoc* variance). The underlying assumption in so doing, on which the advisory process is also based, is that the survey-based TSA assessment gives a close approximation to the true population. Once I have an assessed population, I can derive assessed catch $\left(C_{y}^{A} \text{ and } c_{a,y}^{A}\right)$, landings $\left(L_{y}^{A} \text{ and } l_{a,y}^{A}\right)$ and discards $\left(D_{y}^{A} \text{ and } d_{a,y}^{A}\right)$ from the assessed population estimates by applying firstly the catch equation, and secondly the proportion discarded.

The approach outlined above makes extremely strong assumptions about the future relationships between observed and estimated removals, and between landings and discards. All the comments made in Section 4 regarding the difficulty in predicting discard practice without good models of fleet behaviour apply here also, but in the VIa case I have the additional difficulty of predicting unaccounted removals. In this evaluation I have assumed that these relationships are fixed in the future, but this is not very justifiable and must affect the validity of conclusions to be drawn.

The simulations were initialised using historical data from ICES (2009c), as follows:

- Means of the last three historical values were used in forward simulations for biological metrics such as weights-at-age, natural mortality, proportion mature-at-age, and proportion of F and M occurring before spawning.

- The actual 2009 quota (3520 tonnes) was used in generation of reported landings for the first year of the simulation. Quotas in all subsequent years were the result of the applied management plan.

- Also in the first simulation year (2009), I use reported landings (in other words, the quota) as the intended landings and "true" F as the intended F. In subsequent years these arise from the management plan.

Aside from these added complications, the simulation algorithm is functionally the same as that used for the North Sea haddock MSE (Section 4), to which the reader is referred for details on such aspects as the target-F iterative loop and the sliding F-rule. Legacy code to implement interannual quota flexibility (Needle 2008b) remains in the R-script used for the evaluation, but it is not used in the evaluations presented below.

5.3 RESULTS

Fifty iterations of the future management simulations were carried out for all the requested combinations of target F (0.2, 0.3, 0.4) and TAC constraint ($\pm 15\%$, $\pm 20\%$, $\pm 25\%$), giving nine separate realisations in all. Each iteration was run for 22 years into the future, being the 20 years called for by the Focus Group plus 2 years to allow for quota-setting forecasts. Each realisation took around 4-6 hours to complete, depending on which computer was being used.

Figure 5.2 summarises the historical development of yield for the stock, both the observed yield and the yield estimated by the TSA model (ICES 2009c). The Figure also shows the time-series of CVs for estimated catch, landings and discards: these could be used to generate distributions of starting values for simulations, although this has not been done for this evaluation. Finally, time-series of the ratio between estimated and observed yield are given (referred to here as the "multipliers"). These are close to 1.0 for years prior to 1995, since catch data are included in the assessment for the earlier years, but diverge considerably in more recent years. There is a spike in estimates of unreported landings during the early years of this century, but this has subsequently fallen, perhaps due to the UK Registration of Buyers and Sellers legislation (Scottish Government 2005).

Figure 5.3 shows summaries of mean F, SSB and recruitment for this stock, as estimated by the TSA assessment model (ICES 2009c), along with approximate pointwise 95% confidence intervals. The CVs of these estimates are also summarised. In future work it may be possible to take CVs forward into simulations as part of the assessment uncertainty module.

The results of fitting five stock-recruitment models to historical stock-recruit data from ICES (2009c) are shown in Figure 5.4. Free parameter estimation for both the power and Saila-Lorda models led to fitted curves that were biological implausible, with very high recruitment at very low biomass. Applying a lower bound to parameter estimates for the power and Saila-Lorda models reduces them to the simpler linear and Ricker models respectively. Table 5.2 provides the AIC values for each of these model fits, from which it is clear that the changepoint model has the lowest AIC (and hence is ranked as the best-fitting model). I therefore selected the changepoint model to be used for future simulations.

Finally, Figure 5.5 gives the (almost identical) time-series of log residuals for these model fits. I determined above that I would use the changepoint model, but I also needed to evaluate whether there was any time-series structure to these residuals. Table 5.3 shows the AIC value obtained when fitting a number of ARMA(p,q) models

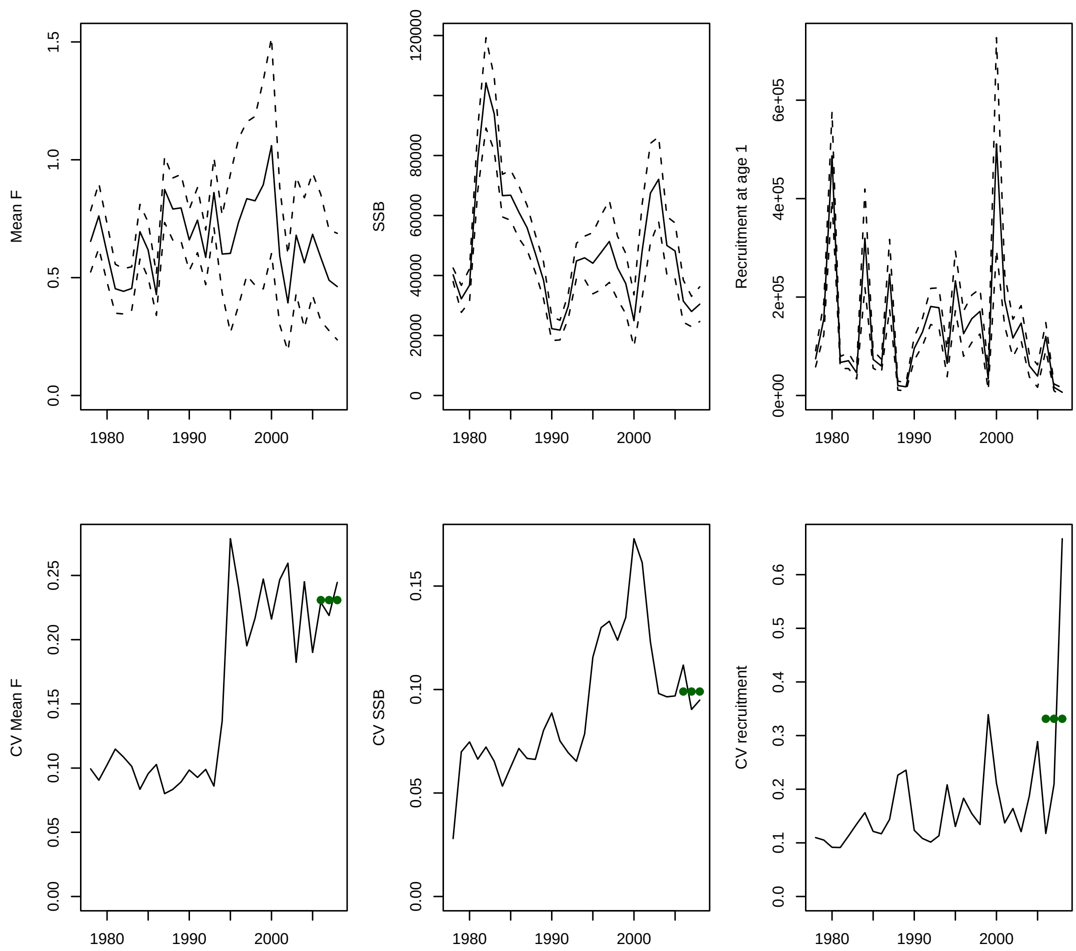


Figure 5.3: Stock assessment results for haddock in ICES Division VIa, from ICES (2009c). Top row: TSA estimates (solid lines) with approximate pointwise 95% confidence intervals (dashed lines) for mean F (left), SSB (middle) and recruitment (right). Bottom row: corresponding CVs. Green dots show the mean of the last three values.

to each time-series, for autoregressive orders $p = 0, \ldots, 3$ and moving-average orders $q = 0, \ldots, 3$. The best fitting model by this criterion is the ARMA$(0,0)$ model: that is, a simple random walk. This fit is not significantly better than the ARMA$(0,1)$ or ARMA$(1,0)$ equivalents (the difference in AIC is much less than 2.0), so there is no strong basis on which to select between these.

However, it may be the case that an unautocorrelated random walk would allow too many large residuals when these are not particularly evident in the recent history of year-class strength. To address this issue, rather than on the basis of strong evidence for it, the simulations discussed below are carried out assuming a ARMA$(1,0)$ time-series of log residuals about the changepoint model. For this time-series model, $r_{t+1} = 0.179 r_t - 0.015$ and $\sigma^2 \simeq 0.970$. These results indicate a fairly weak autoregressive pattern. Examples of these residuals are given in Figure 5.6.

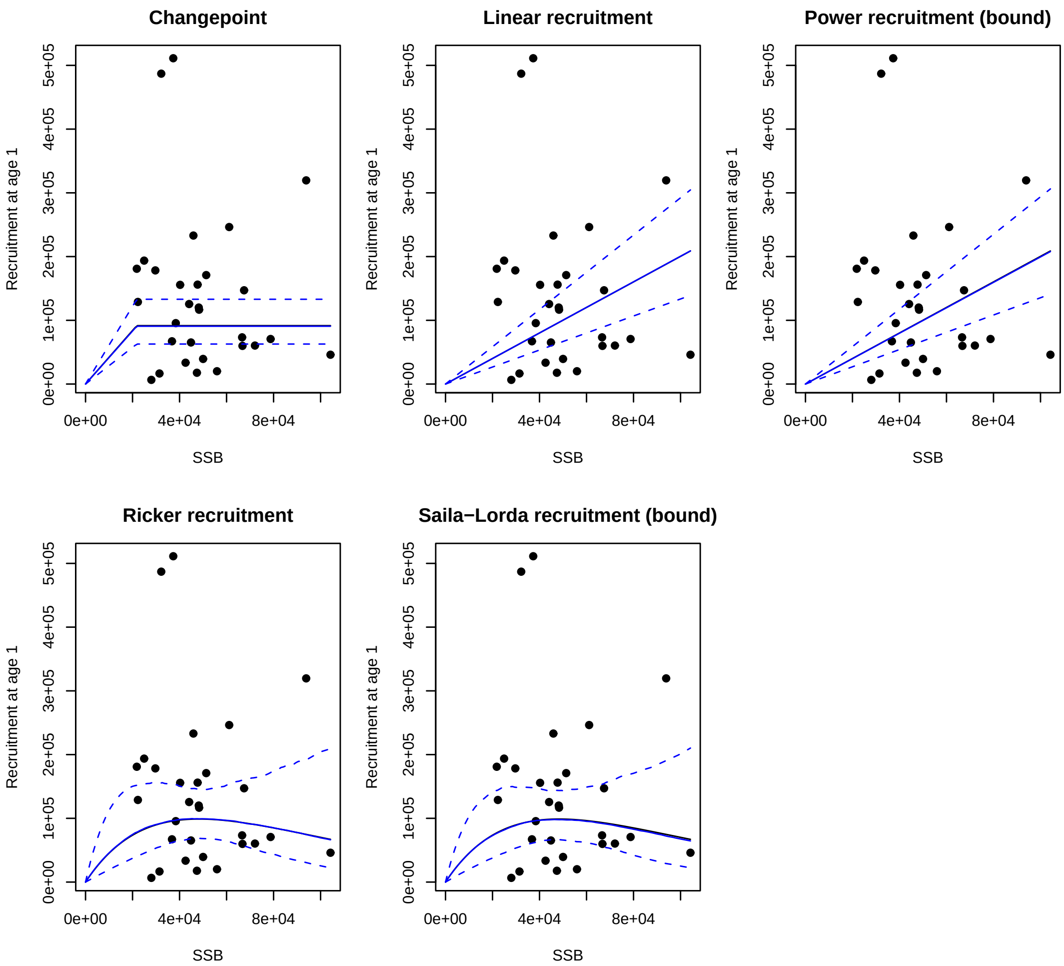


Figure 5.4: Fitted recruitment models for haddock in ICES Division VIa. Stock-recruit data is taken from ICES (2009c). See Table 5.1 for model formulations. Solid lines give fitted models, dashed lines give 95% confidence limits. Note that parameters in both the power and Saila-Lorda model fits were bound below to ensure biological interpretability (power: $\beta \geq 0$, Saila-Lorda: $\gamma \geq 1$).

Figure 5.7 gives a number of summary plots for one realisation of the simulation for which the target $F = 0.3$ and the TAC constraint $= \pm 15\%$ (recall that 50 such realisations were run for each of nine simulations). The time-series of generated recruitment for this example (middle row, right plot) remains at low to moderate levels, and does not (in this case) feature a strong year-class. The corresponding density plot (bottom row, left plot) also demonstrates this lack - on the other hand, this is only one realisation, so too much should not be read into it. Realised mean F (middle row, left plot) oscillates quite vigorously for the first part of the simulation. This is due to the combination of several low years of recruitment, which keeps SSB below B_{lim}, and the clause in the proposed management plan that allows TAC constraints to be waived when SSB is so reduced. The lack of constraint in quota allows mean F to reach high levels for

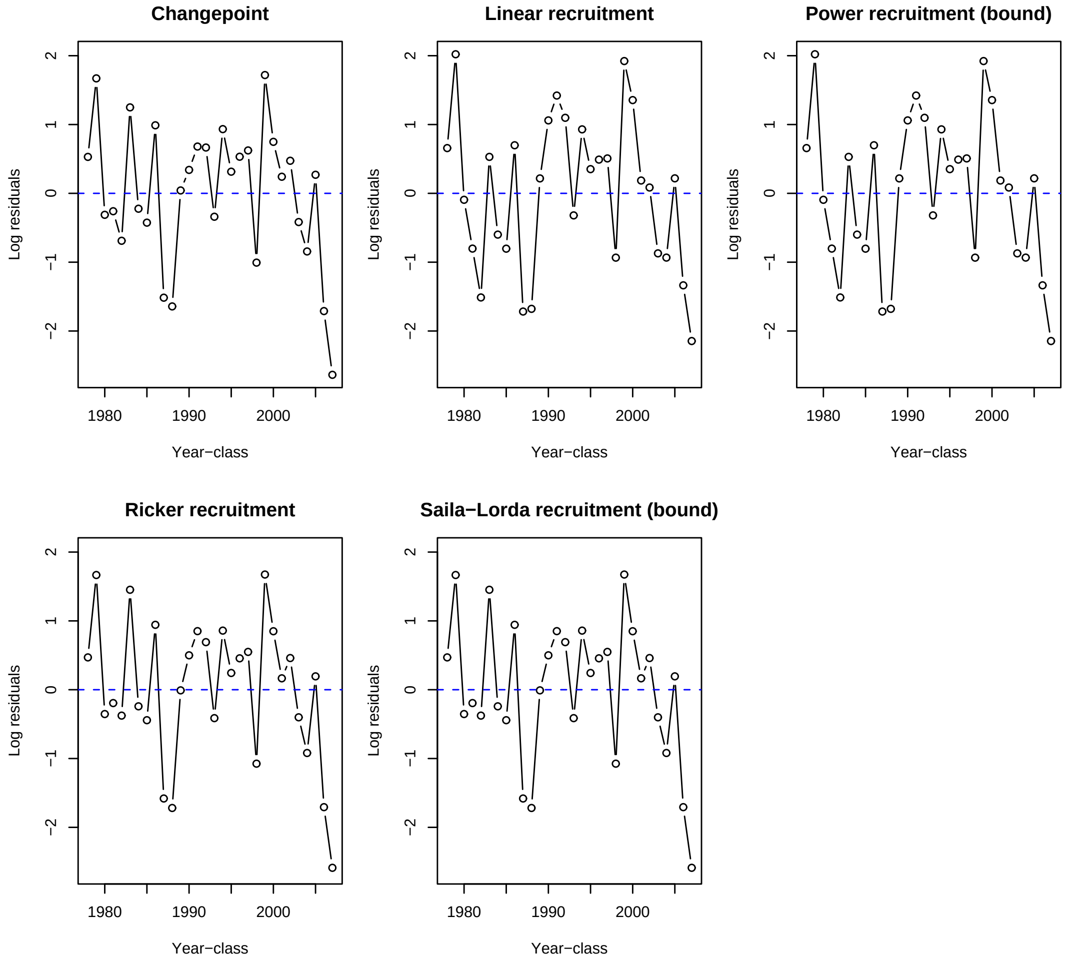


Figure 5.5: Time-series of log residuals from fitted stock-recruit models for haddock in Division VIa.

short time periods. Mean F eventually settles down to fluctuate around the target F level (0.3). The fluctuation is caused by a combination of the following factors:

Implementation lag Each year of the simulation includes a two-year-ahead forecast, the result of which determines what quotas should be for the following year. However, these forecasts contain assumptions about recruitment, and if these are not accurate (as they generally won't be), the permitted quota may be too large or too small for the actual population to which it is applied. If the quota is

	Changepoint	Linear	Power	Ricker	Saila-Lorda
AIC	89.040	94.186	94.186	91.635	91.635

Table 5.2: AIC values for fitted recruitment models.

p	q	AIC	p	q	AIC
0	0	89.040	1	2	92.552
0	1	90.154	3	0	93.023
1	0	90.268	1	3	93.634
0	2	91.717	3	1	93.663
0	3	91.879	2	2	94.282
2	1	92.206	3	2	95.629
2	0	92.233	2	3	95.632
1	1	92.291	3	3	97.595

Table 5.3: AIC values (in ascending order) from fitting ARMA(p,q) models to log residuals from the changepoint recruitment model.

taken regardless, this will result in realised mean F that is higher or lower than intended.

The TAC constraint Fixing the amount by which quotas can change from year to year will also hinder achievement of the target F. In a situation of rising (or falling) stock size, the quota is not allowed to rise (or fall) commensurately, and realised mean F is affected as a result.

Even with these fluctuations, the average F over the later simulation period is consistently lower than the historical average (Figure 5.3). Recruitment strength remains low to moderate in this run. SSB continues to fall initially and then rises steadily. This pattern is facilitated by the lower realised F: this allows the moderate recruitments that do occur to survive to adulthood. Permitted quota (top row, middle plot) follows an overall slowly-ascending trajectory (save for a temporary jumps in years when the TAC constraint is removed), with true landings, discards and catches all following suit according to the fixed relationships between them. The interannual change in quota (bottom row, right plot) is at the maximum permitted value for the majority of years in the simulation.

Staying with the same evaluation (target $F = 0.3$, TAC constraint $\pm 15\%$), Figure 5.8 summarises all 50 simulation iterations. The median values from these plots are essentially the result of smoothing across different realisations of recruitments, and are therefore only useful as an indication of likely future events. Given this caveat, the simulations indicate that SSB is likely to rise initially before stabilising at or around 80 to 90 kt, mean F is likely to fluctuate considerably around the target level (but should in any case be able to remain low on average), and landings will rise steadily and (broadly speaking) as fast as the quota constraint allows.

I can summarise risk from these simulations in two ways. The first is to consider the

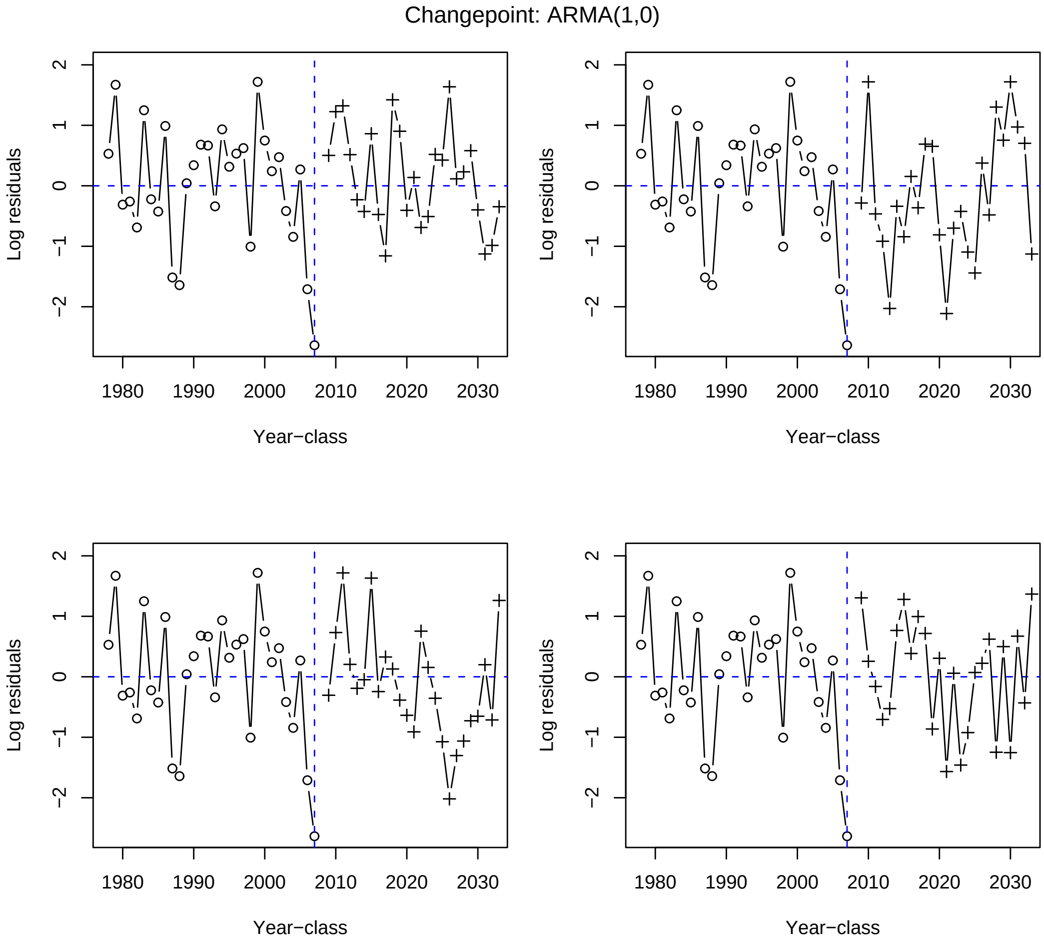


Figure 5.6: Examples of stochastically-generated time-series of log-residuals to the fitted changepoint model for haddock in Division VIa. Values to the left of the vertical blue line are observed historical log residuals, while those to the right are values generated by an ARMA$(1,0)$ model.

true biomass values from all 50 iterations for a given year, and calculate the proportion of those values which lie below B_{pa} or B_{lim}. Doing this for each year of the same run as above (target $F = 0.3$, TAC constraint $\pm 15\%$) results in Figure 5.9 which shows that the risk is small after the initial three or so years of recovery (although the risk does average around 5% towards the end of the time-series).

The second method is to consider each iteration separately, and count the number of years in that iteration for which biomass was less than B_{pa} or B_{lim}. This provides a different type of inference that some managers may find more intuitive, and I will focus on it for the remainder of our discussion. The results of this analysis for all nine evaluation runs are summarised in Table 5.4, and Figures 5.10 and 5.11.

The ways in which the TAC constraint and target F affect risk and yield are complicated and worthy of closer consideration. Figure 5.10 suggests that, for a $\pm 15\%$

TAC constraint, the risk declines between $F = 0.2$ and 0.3, before increasing again for $F = 0.4$. This perception is more a function of the loess curve that has been plotted, rather than related to the actual risk: Table 5.4 shows that the risk is approximately equal for $F = 0.2$ and 0.3. Note, however, that yield shows a definite peak at $F = 0.3$ for all TAC constraints (Table 5.4 and Figure 5.11), which concurs with general perceptions that F_{msy} for haddock is around 0.3 (ICES 2007c). The original EC request called for a comment on "the extent to which the application of this rule would deliver maximum sustainable yield from the stock": on the basis of these results, and assuming that F_{msy} is indeed around 0.3, then fishing at this level appears to result in higher cumulative yield than either higher or lower fishing mortalities, no matter what the TAC constraint. Returning to Figure 5.10, target F has less effect on risk when the TAC constraint is 20% - in this case, however, the cumulative yield is very much less for an F of 0.2 than for either 0.3 or 0.4 (Figure 5.11). The pattern of risk when the TAC constraint is 25% is similar to that for the 15% case (Figure 5.10), and the cumulative yield shows a maximum at $F = 0.3$.

Run	Target F	TAC cons	Years $B < B_{\mathrm{pa}}$	Years $B < B_{\mathrm{lim}}$	Cumulative yld
1	0.2	15%	3.76	0.80	703544.4
2	0.3	15%	3.70	0.94	789485.8
3	0.4	15%	6.24	2.34	667363.2
4	0.2	20%	3.60	1.04	663931.1
5	0.3	20%	4.40	1.10	804322.1
6	0.4	20%	4.70	1.18	785020.7
7	0.2	25%	3.46	0.86	711195.9
8	0.3	25%	4.00	1.08	806573.7
9	0.4	25%	6.26	2.20	775960.1

Table 5.4: Summaries of risk (number of years in each iteration for which biomass is less than reference points, averaged over iterations) and cumulative yield (summed true landings in tonnes, averaged over iterations) for each of the nine 20-year simulation runs for the VIa haddock MSE.

5.4 Conclusions

This evaluation proved to be difficult to complete. While the example of the North Sea haddock MSE (Section 4) was a useful template, there were considerable additional coding issues to be solved, caused principally by the need to mimic the mostly survey-based TSA stock assessment method used by the ICES WGNSDS and WGCSE groups to assess the stock (ICES 2009c). Aside from these issues, there were real difficulties in deciding how to deal with discards and other unaccounted removals in the future simulations. These have been circumvented in the evaluation by assuming that the proportions in the total catch of all such removals remains constant into the future: without better models of fleet behaviour, it is hard to see how this approach could be improved, but the assumptions about future removals remain crude and this must have an effect of the utility of the conclusions reached. It did not prove to be possible to implement the code in the new version of FLR, which is unfortunate as this would have run much more quickly and removed concerns over the small number of simulations on which the extant results are based (but see Section 6).

The example of VIa haddock presents the same problem as that of North Sea haddock, namely difficulties in forecasting discards without good models of why fishermen discard in the first place. However, it also features the additional issue of how to deal more widely with unaccounted removals, which may be caused by misreported or unreported catch, changes in natural mortality, or changes in survey catchability, as well as discards. It therefore emphasises, perhaps even more strongly than the North Sea haddock case, the need for improved models of fleet behaviour. Without these, the utility of advice based on management simulations must always be compromised.

The conclusion of the evaluation presented in Needle (2010a), given these caveats, was as follows. The simulations carried out suggested that the proposed management plan for haddock in Division VIa is likely to be sustainable. Over all tested combinations of target F (0.2, 0.3, 0.4) and TAC constraint ($\pm$15%, $\pm$20%, $\pm$25%), spawning-stock biomass was below B_{pa} for less than seven of the 22 years in the future simulations (on average). The bulk of these years occurred during the first years of the simulations as the stock recovered from its current low state. Biomass was below B_{lim} for less than three years in the simulations (on average), and these were nearly always during the first years of recovery. Cumulative yield is also likely to increase under the plan, although the relationships between target F, TAC constraint and yield are complicated. The simulations suggest that a target F of 0.3 has the best chance of producing the combination of high cumulative yield and low risk to biomass. It should be noted that, at the time of writing (March 2012), Scottish fisheries managers have been keen to avoid implementation of this plan, viewing the 25% TAC constraint as being too restrictive for the current state of the stock and fishery.

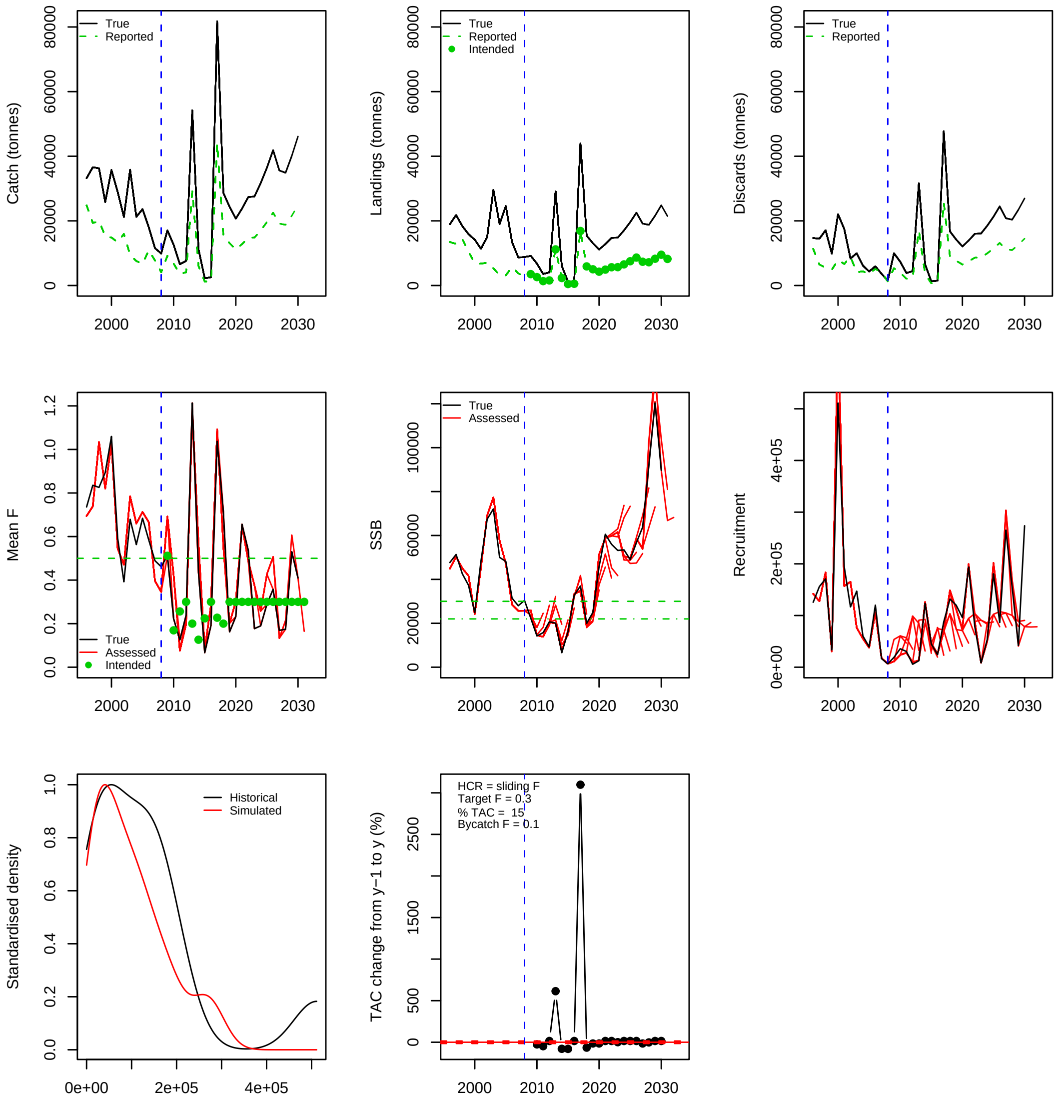


Figure 5.7: Summary plots for one realisation of the VIa haddock MSE. Here the target F is 0.3, and the TAC constraint is $\pm 15\%$. For all plots, the vertical blue line denotes the last historical year. Top row: total catch (left), landings (middle) and discards (right), showing true and reported values (and intended values, for the landings plot). Middle row: time series of mean F (left), SSB (middle) and recruitment (right). The true values are given in black, while the assessed values from each year of the forward simulation are shown in red. Green dots indicate the intended mean F in the left-hand plot. Green lines show reference points for mean F and SSB. Bottom left plot: comparison of standardised frequency distributions for historical and simulated recruitment. Bottom right plot: percentage interannual change in quota, with $\pm 15\%$ limits highlighted by red dashed lines.

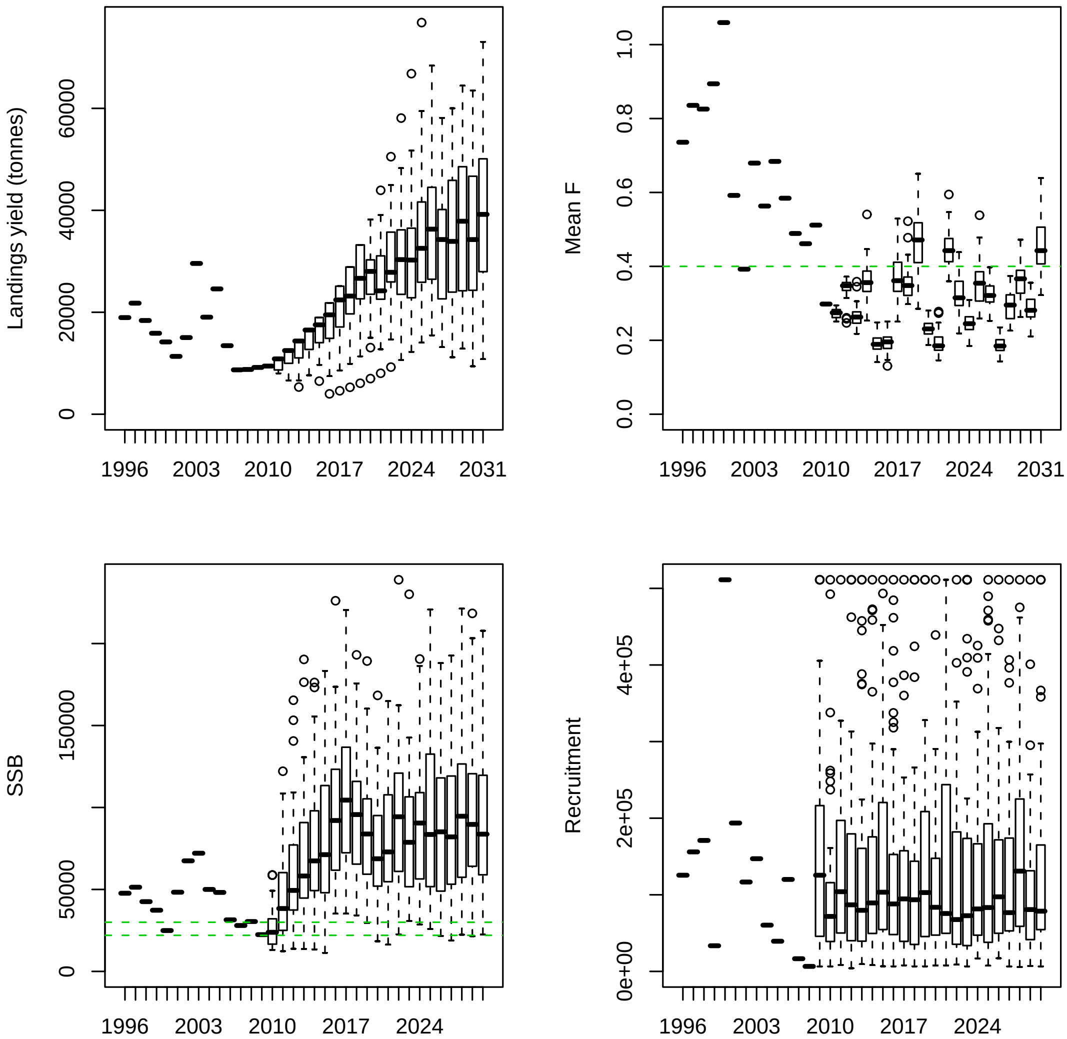


Figure 5.8: Summary plots of 50 simulation iterations of the haddock VIa MSE, with target $F = 0.3$ and TAC constraint of $\pm 15\%$. The short horizontal lines indicate the medians, and the boxes the quartiles (25%ile and 75%ile). The lower whisker gives the value of $25\%\text{ile} - (1.5 \times (75\%\text{ile} - 25\%\text{ile}))$ and the upper gives $75\%\text{ile} + (1.5 \times (75\%\text{ile} - 25\%\text{ile}))$. Outliers beyond this range are shown by open circles. The dashed line on the top-right plot shows the target F, while those on the bottom-left plot show B_{pa} (upper) and B_{lim} (lower). Historical estimates (pre-2009) are shown as short horizontal lines only.

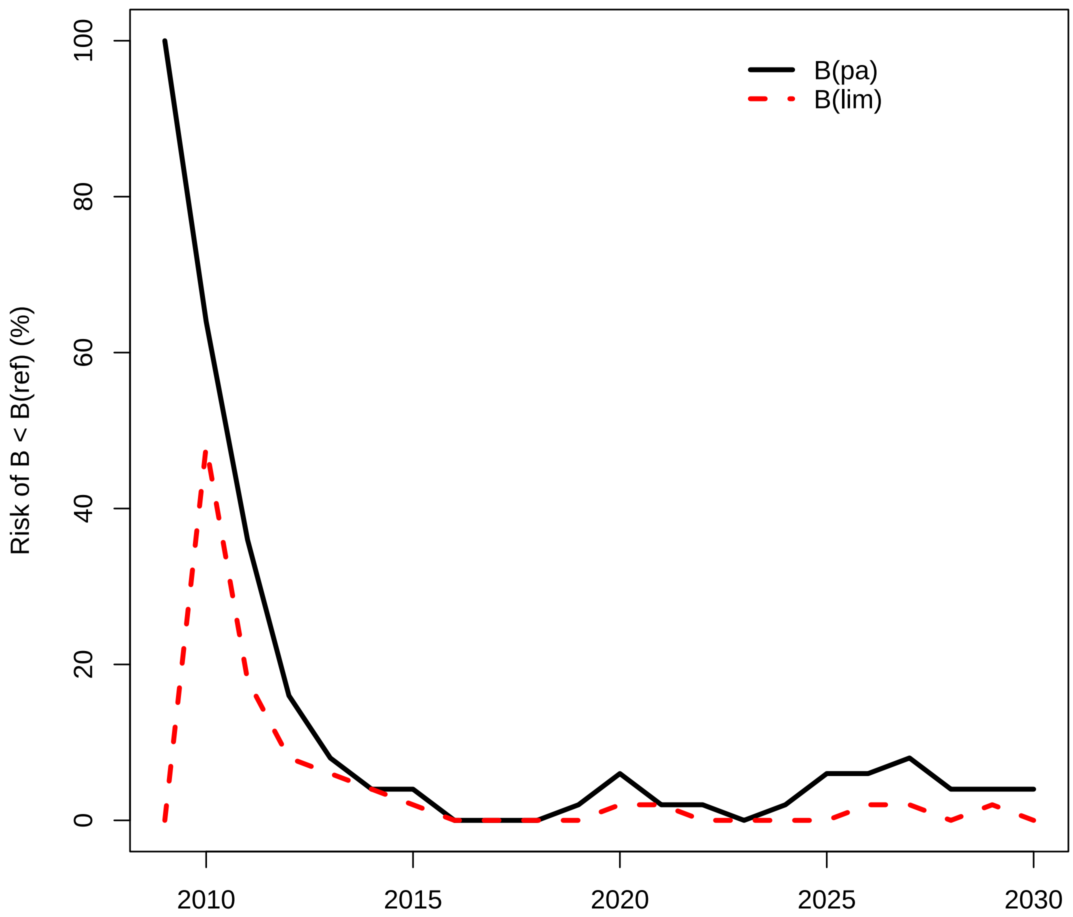


Figure 5.9: For each year of the VIa haddock MSE run with target $F = 0.3$ and TAC constraint $\pm 15\%$, the percentage of 50 iteration runs for which true biomass is less than B_{pa} (black line) or B_{lim} (red line). In the first year of the simulation, biomass lay between B_{pa} (black line) and B_{lim}.

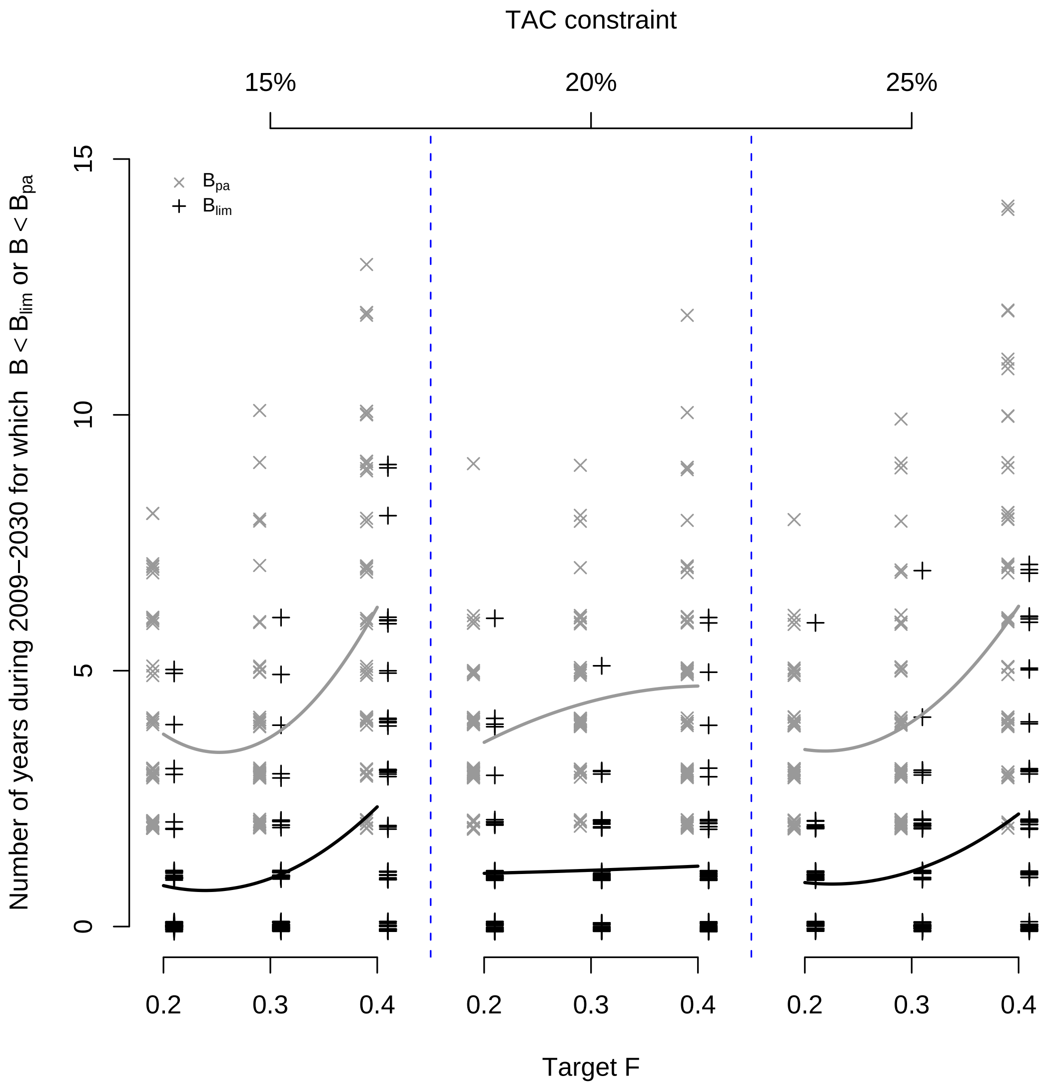


Figure 5.10: Summary of risk of $B < B_{\mathrm{pa}}$ (grey) and $B < B_{\mathrm{lim}}$ (black) for different values of the target F and TAC constraint, from the VIa haddock MSE. Risk is measured here by the number of years (out of 22 simulation years) for which spawning stock biomass $B < B_{\mathrm{pa}}$ or $B < B_{\mathrm{lim}}$ as appropriate. The correspondingly-coloured solid lines show the fits of loess smoothers to the full time-series of risk estimates (so the grey line is a smoother fitted to all the grey crosses, while the black line is fitted to all the black crosses). Small random perturbations have been applied to the vertical position of each cross to improve visualisation.

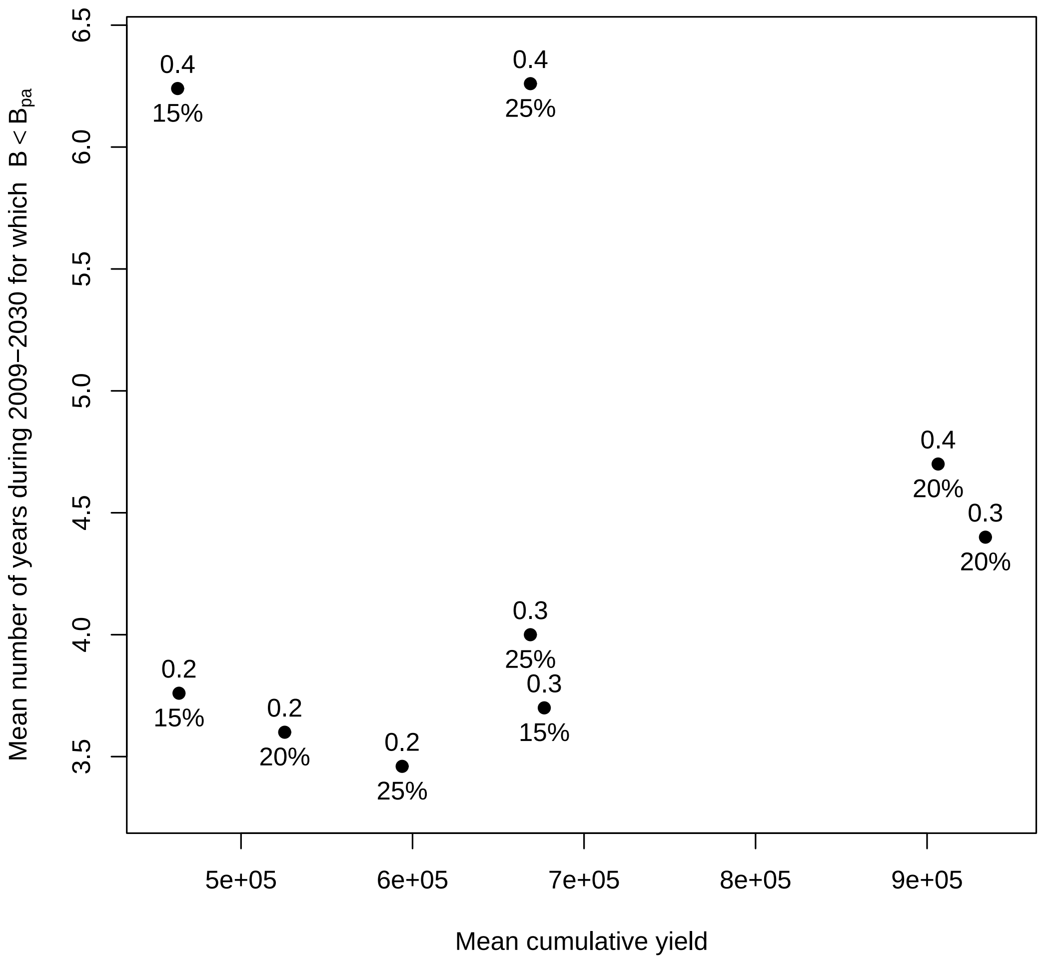


Figure 5.11: Risk against mean cumulative yield for all nine runs in the VIa haddock MSE. Numbers indicate the target F (upper) and TAC constraint (lower) used in each case. Risk is measured here by the number of years (out of 22 simulation years) for which spawning stock biomass $B < B_{\mathrm{pa}}$. Cumulative yield is the summed true landings from each iteration, averaged over iterations.

6 Management strategy evaluation for Rockall haddock

This section is based on analyses first presented in Needle and Mosqueira (2011). My co-author in this paper (Iago Mosqueira, EC Joint Research Center, Ispra, Italy) has confirmed that the methods, results and analyses presented here are solely my own work (see page 5). I include the analysis here as it builds further on those presented in Sections 4 and 5, adding the ability to base evaluations on many more iterations than before.

6.1 INTRODUCTION

Discussions between the European Union (EU) and the Russian Federation (RF) on possible joint management measures for the Rockall haddock fishery have been progressing for over ten years. Changes in the shape of the EU Exclusive Economic Zone in 1999 led to the renewal of the RF Rockall haddock fishery, and as this fishery has quite different characteristics from the (predominantly) Scottish and Irish fisheries already present in the area, it was clear that joint management would be both necessary and potentially difficult to implement. Meetings involving both scientists and fisheries managers from the EU and the RF have been held on an almost annual basis since 2001 to determine what is known about these fisheries, and how such information can best be used to develop a productive and sustainable management system.

Building on the history of Rockall fisheries and the supporting scientific work presented by Newton et al. (2008), the EU-RF Working Group on Rockall haddock met four times during 2008-2010 and produced a state-of-the-art review of available data and scientific analyses pertaining to Rockall haddock (European Commission and Russian Federation 2009). At the fourth of these meetings, in Edinburgh during September 2010, a proposal for a joint EU-RF management plan for Rockall haddock was drafted. Following further refinements, a final version was presented to the appropriate North East Atlantic Fisheries Commission (NEAFC) plenary meeting towards the end of 2010. The decision was taken there to forward the proposal to ICES for evaluation: the text of the request is given in Section 6.2 below.

Although the request was received by ICES towards the end of 2010, technical difficulties with the evaluation and pressure of other work meant that the response to the request could not be included as part of the June 2011 advice release. This Section provides a quantitative risk-based evaluation of the likely performance of the proposed management plan, although it does not cover all relevant issues as yet. Remaining problems are highlighted in the text and will be dealt with during any future revisions of the management plan (if implemented). I implemented the evaluation in the R programming system (R Development Core Team 2011, version 2.13.0), using the most recently-available versions of the FLR libraries (FLR Team 2006, Kell et al. 2007, Hillary 2009, `http://flr-project.org/`).

The key development in this work, when compared with the North Sea and West of Scotland haddock MSEs discussed in Sections 4 and 5, is the implementation of a new version of the FLR analysis libraries, to be released formally in October 2011. Although quite difficult to use, the numerical estimation modules now provided in FLR are several orders of magnitude faster than the bespoke routines developed for the previous MSEs (Sections 4 and 5). This enables much more complete coverage of distributions of output quantities (and therefore risk), and improves the robustness of conclusions to process and model uncertainty.

6.2 Request to ICES from NEAFC regarding the proposed Rockall haddock LTMP

NEAFC requested ICES to evaluate the following proposal for the harvest control component of a long-term management plan for Rockall haddock and in particular to consider whether the plan is consistent with the precautionary approach and will provide for the sustainable harvesting of the stock. ICES was also asked to suggest an alternative approach if necessary.

Draft EU-Russia proposal for harvest control component of a long-term management plan for haddock at Rockall

In the following, the TACs refer to total catches, not just landings.

1. Every effort shall be made to maintain a level of Spawning Stock Biomass (SSB) greater than B_{pa} and a minimum level of SSB greater than B_{lim}.

2. For [20XX] and subsequent years the Parties agreed to set a TAC to be consistent with a fishing mortality rate F_{target} of no more than [either F_{pa} (0.4) or F_{msy} (0.3)] for appropriate age-groups, when the SSB in the end of the year in which the TAC is applied is estimated above B_{pa}.

3. The Parties agree that the TAC that results from the application of the fishing mortality referred to in paragraph 2 will be adjusted according to the following

formula:

$$\mathrm{TAC}_y = \mathrm{TAC}_f + 0.2\left(\mathrm{TAC}_{y-1} - \mathrm{TAC}_f\right)$$

where TAC_y is the TAC that is to be set by the management plan, TAC_{y-1} is the TAC that was fixed the previous year and TAC_f is the TAC resulting from the provisions in paragraphs 1 and 2.

4. Where the SSB referred to in paragraph 2 is estimated to be below B_{pa} but above B_{lim} the TAC shall not exceed a level, which will result in a fishing mortality rate equal to $F_{\mathrm{target}} - \left(F_{\mathrm{target}} - 0.1\right)\left(B_{\mathrm{pa}} - \mathrm{SSB}\right) / \left(B_{\mathrm{pa}} - B_{\mathrm{lim}}\right)$. This consideration overrides paragraph 3.

5. Where the SSB referred to in paragraph 2 is estimated to be below B_{lim} the TAC shall be set at a level corresponding to a total fishing mortality rate of no more than 0.1. This consideration overrides paragraph 3.

6.3 Specific modelling issues for Rockall haddock

The code used previously for haddock MSEs (Needle 2008b, Needle 2008c, Needle 2010a, Sections 4 and 5, and Chapter VI) could have been modified to run the Rockall haddock MSE, but it presented two significant problems. Firstly, much of it was bespoke code written to implement features that were not present in the early version of FLR that was available at the time, and such code would have been very difficult for reviewers to understand and check for errors. Recent developments in FLR have in any case rendered much of this bespoke code obsolete. Secondly, the previous code was not optimised for speed, and a single 100-iteration simulation run could take over 15 hours (thus limiting the scope of sensitivity analyses). The new version of FLR features a number of optimised analysis algorithms which reduce runtimes dramatically: the same 100-iteration simulation run now takes around 8 minutes.

For these reasons, the Rockall haddock MSE described here does not build directly on previous haddock MSEs, but rather on MSEs developed for other species using the development version of FLR (to be released in October 2011 as version 2.4). As is usually the case, the code for these MSEs could not be used without modification for Rockall haddock, due to specific features of the stock, assessment and proposed management plan, and further code development was required. However, the programming approach used in the new version of FLR is not particularly intuitive or easy to use, so the development was not without problems initially. Furthermore, the MSE does not implement all the features of the system that could be considered, particularly the presence of two different fleets with different catachability characteristics. The intention expressed by Needle and Mosqueira (2011) was that the evaluation would be a live code that would develop in the future and be used for evaluations of subsequent revisions to the proposed management plan. It is worth noting that the North Sea haddock MSE (Needle 2008b, Needle 2008c, Section 4 and Chapter VI) took over two years to develop, a much greater period of time than has been devoted thus far to the Rockall haddock MSE.

6.3.1 Recruitment

Recruitment dynamics for haddock in the North Sea and West of Scotland are characteristically sporadic: that is, there is a strong tendency in those stocks for very occasional large year-classes interspersed with several weak year-classes. Recruitment for Rockall haddock appears to have a stronger relationship with parental spawning stock biomass, as indicated by Figure 6.1. Therefore, a Ricker stock-recruit model was used to generate stochastic recruitments in the biological simulation model under-pinning the evaluation. This model is given by

$$R_y = \alpha S_{y-1} \exp\left(-\beta S_{y-1}\right) \exp\left(\varepsilon^R_{y-1}\right), \tag{6.1}$$

where R_y is recruitment at age 1 in year y, S_{y-1} is the parental spawning stock biomass in year $y-1$, α and β are fitted parameters, and $\varepsilon^R_{y-1} \sim N\left(0, \sigma^2_R\right)$ where σ_R is the assumed recruitment standard deviation. Within the knowledge production model (see Figure 1.1), a simple three-year geometric mean of previous recruitment was used as the best estimate of incoming year-class strength. In the real assessment (ICES 2011d), a survey-based RCT3 prediction is used to generate recruitment estimates for the intermediate year, while a long-term (1991 onwards) geometric mean is used for the quota year. These refinements could be included in a future revision of the MSE.

6.3.2 Stock assessment

The Rockall haddock assessment (ICES 2011d) is carried out at the ICES assessment working group using the original MS-DOS implementation of XSA (Shepherd 1992, Darby and Flatman 1994). The version of the model provided with FLR (FLXSA; Kell 2011) is functionally identical to XSA, and has the advantage that it can be built into MSE simulation loops. For this reason, FLXSA is used here to generate the simulated stock assessment on which management decisions are taken. The same run settings are used as for the XSA assessment in ICES (2011d), namely:

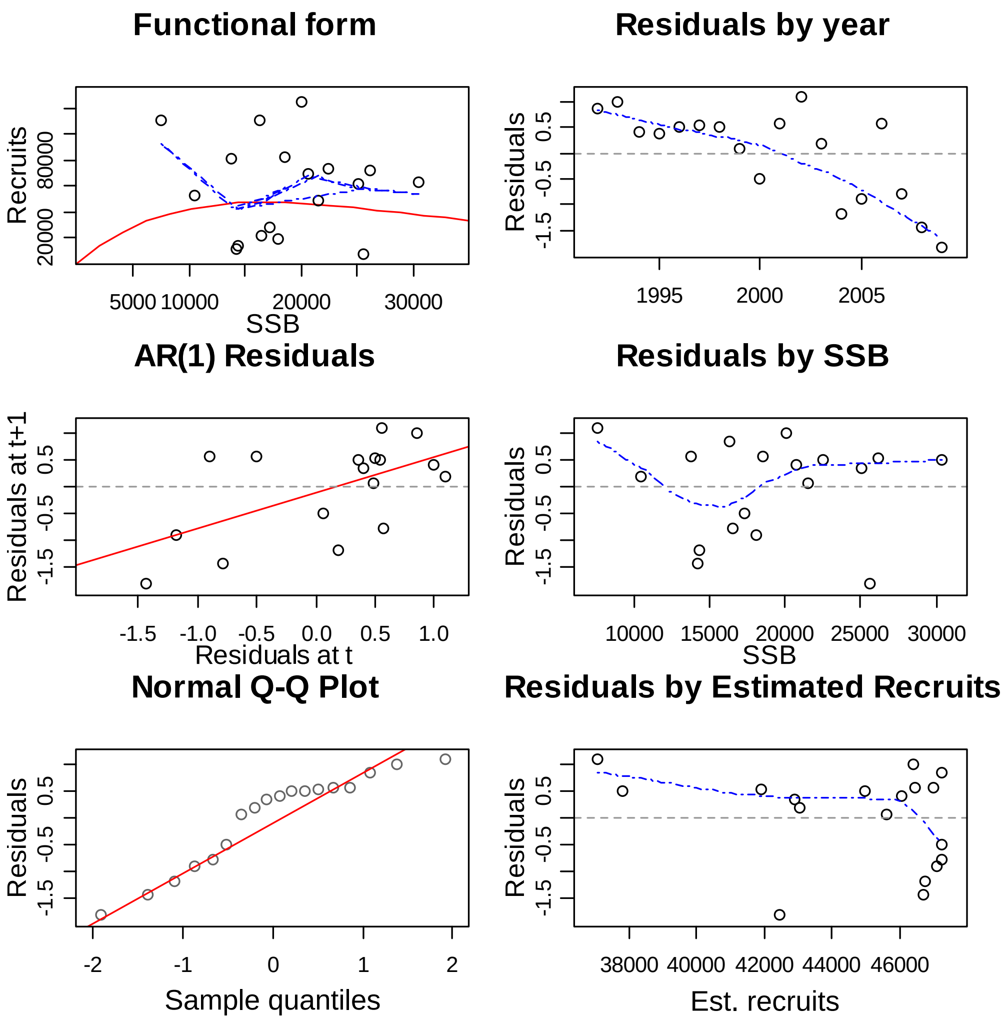


Figure 6.1: Diagnostics for Ricker stock-recruit model. The fitted Ricker curve is shown in the top-left plot (red line), along with comparative non-parametric loess smoothers (blue lines). The remaining diagnostics are self-explanatory.

- Tuning indices: one survey index (SCOGFS).
- Time-series weights: none.
- Catchability dependent for ages < 4.
- Regression type: C.
- Catchability plateau: 5.
- Shrinkage standard error: 1.0.
- Shrinkage age-year: 3 ages, 4 years.
- Minimum standard error: 0.3.
- Plus group: 7+.
- Mean F age range: 2-5

The summary outputs from the FLXSA run on historical data are given in Figure 6.2 (stock summary) and 6.3 (residuals).

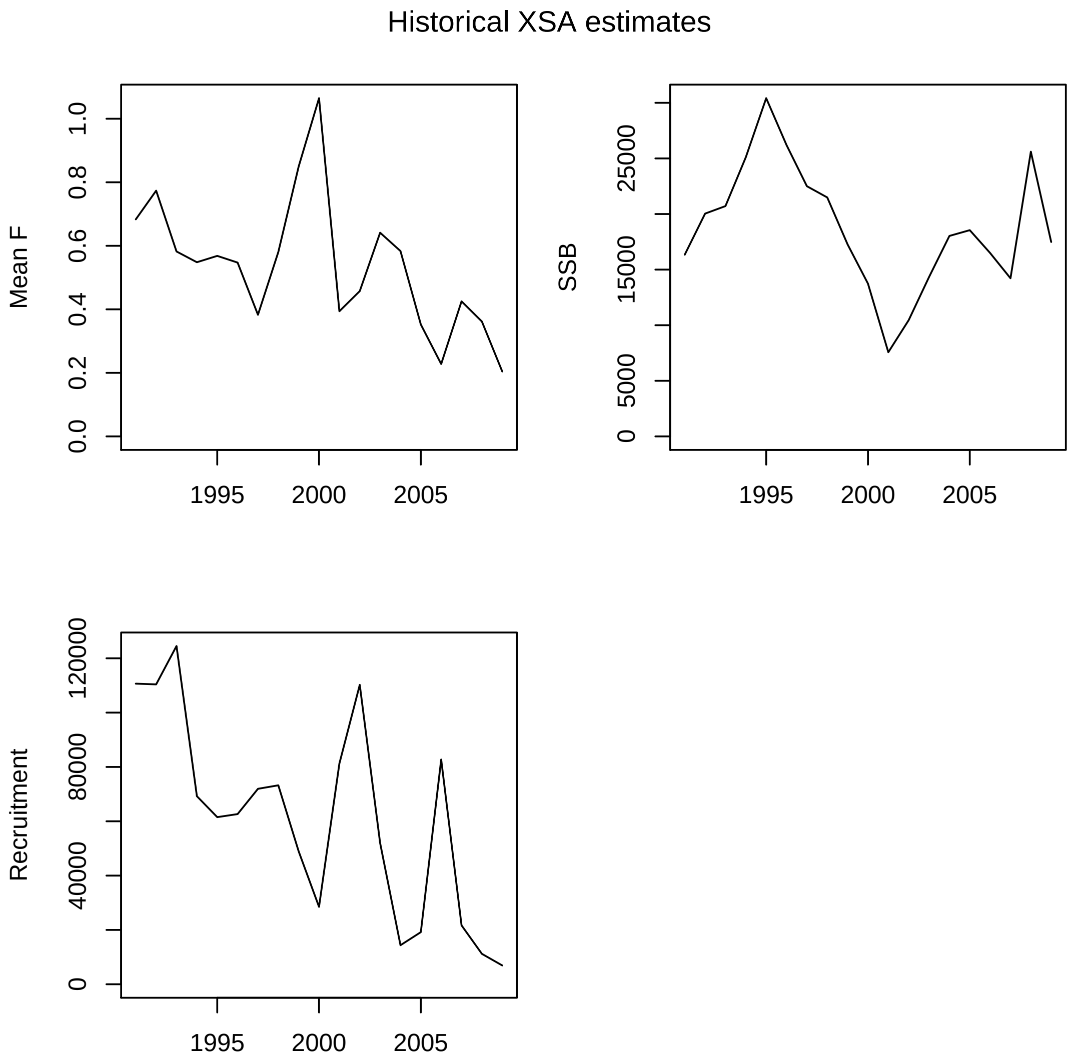


Figure 6.2: Summary results of the FLXSA assessment applied to historical Rockall haddock data.

The assessment makes no explicit distinction between reported landings and estimated discards, which are summed together to give total catch. In the simulation forecast, the ratio of landings to discards for each age is assumed to be fixed. In previous work on MSEs for haddock (see, for example, Section 4), it has been demonstrated that this assumption can lead to problems (generally underestimation of SSB) with the simulated assessment, particularly when a large year-class is generated. This difficulty may still arise for Rockall haddock, but the magnitude of the effect is likely to be less as the quota is assumed to apply to total catch rather than just landings (see Section 6.2). I also note that the Russian fleet is thought not to discard any fish. Hence the assumed split between landings and discards is less germane to the simulated stock and fishery dynamics.

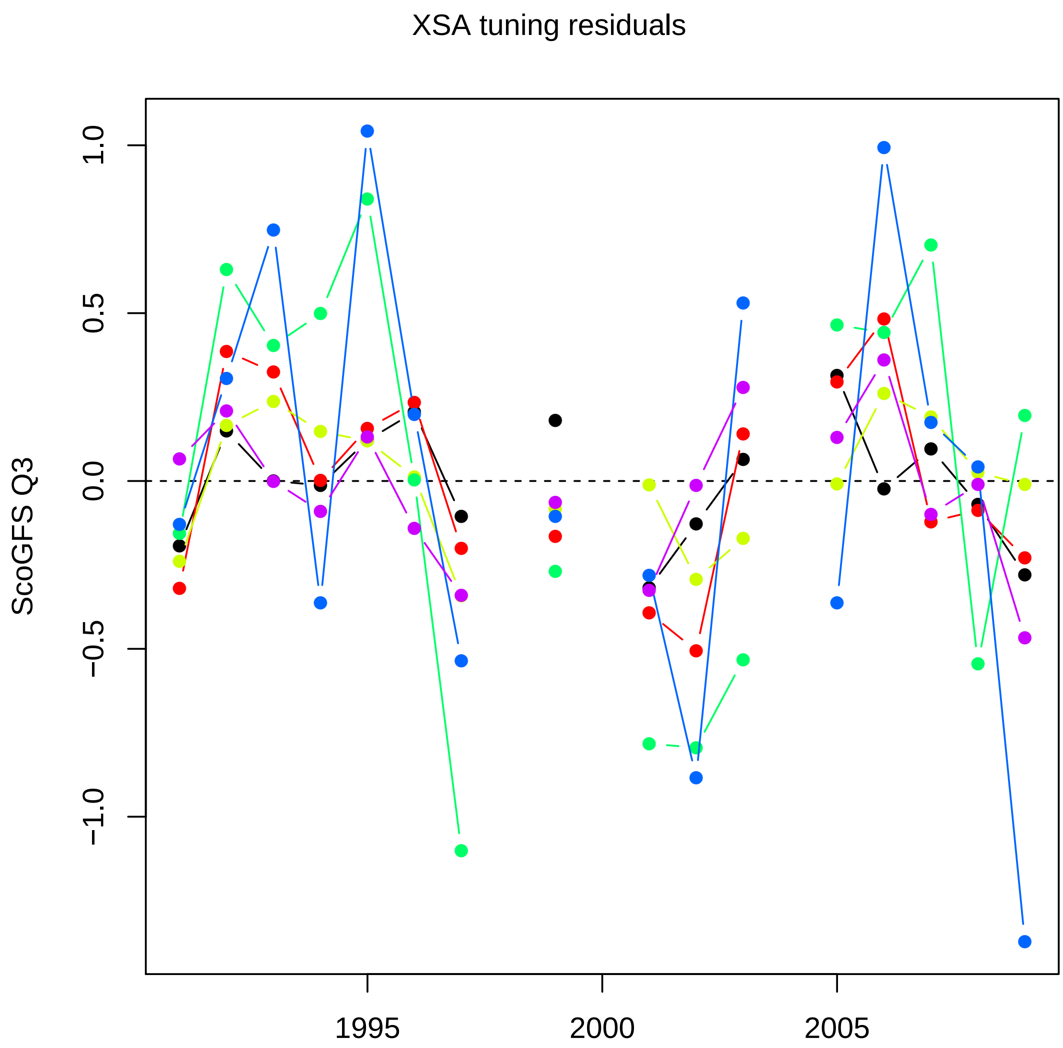


Figure 6.3: Survey-index catchability residuals from the FLXSA assessment applied to historical Rockall haddock data.

The simulations were initialised using historical data, as follows:

- Means of the last three historical values were used in forward simulations for biological metrics such as weights-at-age, natural mortality, proportion mature-at-age, and proportion of F and M occurring before spawning.

- The actual 2010 quota (4997 tonnes) was used in generation of total catch for the first year of the simulation. Quotas in all subsequent years were the result of the applied management plan.

- Also in the first simulation year (2010), I used total catch (in other words, the quota) as the intended catch and "true" F as the intended F. In subsequent years these arise from the management plan.

Aside from these added complications, the simulation algorithm is functionally similar to that used for the North Sea haddock MSE: see Section 4, to which the reader is referred for details on such aspects as the target-F iterative loop and the sliding F-rule.

6.3.3 Research-vessel survey indices

The ICES assessment for Rockall haddock uses indices from one research-vessel survey (the Scottish Q3 groundfish survey), which has been conducted annually since 1991 (save for three years during which the survey did not take place). Figure 6.4 gives the time-series of the survey indices for each age, along with distributions of the same indices but with stochastic noise applied. For a survey index datum $I_{a,y}$ for age a in year y, in the kth iteration, the stochastic version is generated using

$$\tilde{I}_{a,y,k} = I_{a,y} \exp\left(\varepsilon^{I}_{a,y,k} - \frac{1}{2}\sigma_I^2\right), \tag{6.2}$$

where $\varepsilon^{I}_{a,y,k} \sim N\left(0, \sigma_I^2\right)$ and $\sigma_I = 0.3$ is the assumed survey standard deviation. Figure 6.5 shows the resultant distributions of assessed mean fishing mortality, SSB and recruitment when K assessments are run using the K stochastically-generated survey index time-series.

Survey indices must also be generated for each year in the future simulations, to enable these to include stock assessments. The historical relationship between estimated abundance $N_{a,y}$ and survey indices $I_{a,y}$ for each age was generated by fitting straight lines to logged values,

$$\ln I_{a,y} = \gamma_a + \eta_a \ln N_{a,y}. \tag{6.3}$$

These relationships are illustrated in Figure 6.6. In each year y of each future simulation, the required survey indices were then generated using

$$I_{a,y,k} = \gamma_a \mathrm{e}^{\eta_a N_{a,y,k}} \varepsilon^{I}_{a,y,k}. \tag{6.4}$$

6.3.4 Maximum fishing mortality

In the FLR implementation used here, true simulated fishing mortality has an upper bound of 2.0. This can be reached (very occasionally) in the simulations following (it would appear) a combination of an increasing trend in fishing mortality, limited scope to match quota to stock abundance (due to a constraint of interannual variation in quota), and a coincidental run of relatively low recruitments. This is not a common

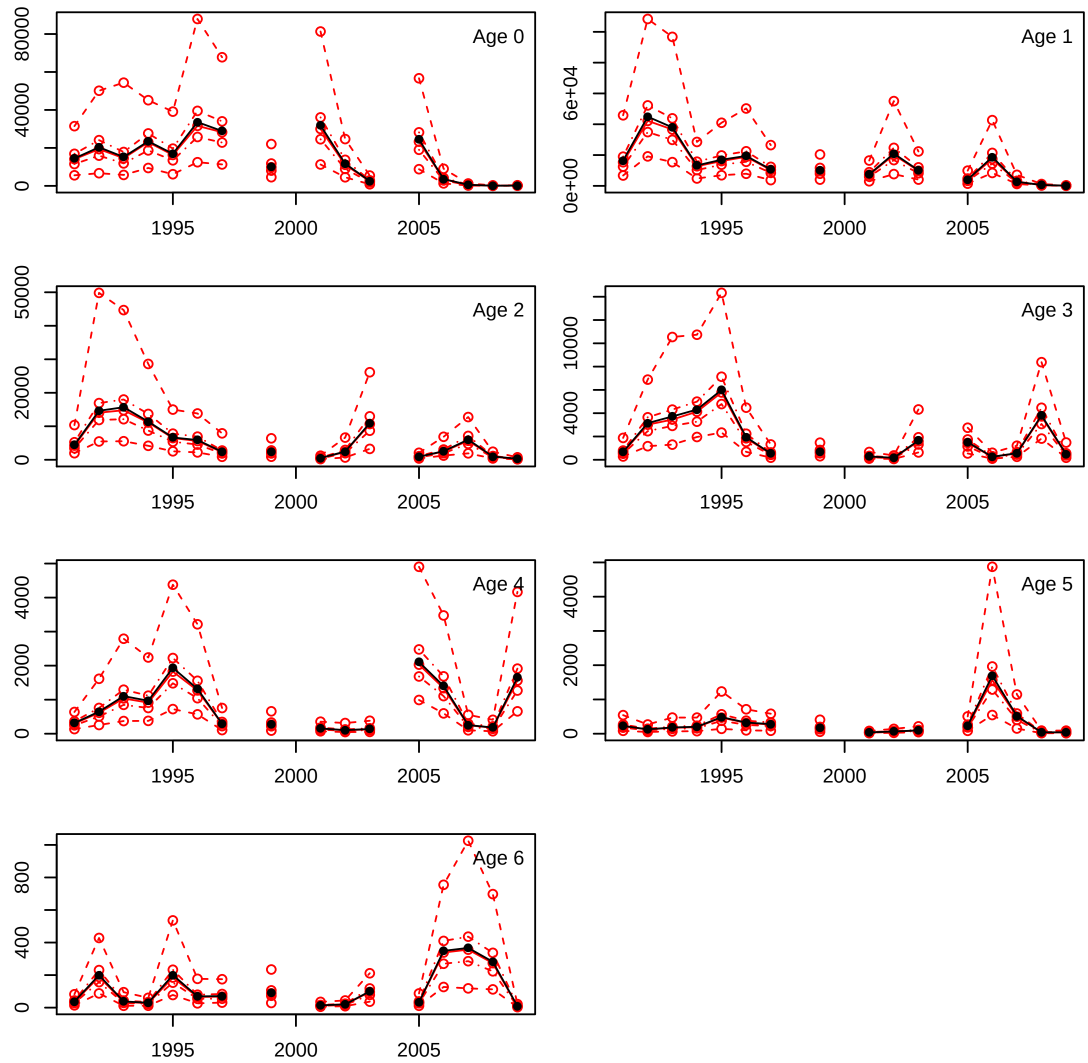


Figure 6.4: Time-series of Rockall haddock ScoGFS Q3 survey abundance indices for each age. Black lines: observed indices. Red lines: percentiles (5%, 50%, 95%) of $K = 500$ indices with stochastic noise applied (see Equation 6.2).

occurrence: for the 500 simulations with a target F of 0.3 reported below, the maximum F was reached in only 9 (0.018%) iterations. However, as Figure 6.8 shows, the high true F does not appear to be immediately reflected in a high assessed F, so it is not clear that managers would be aware of the effect were it to occur in reality. The summary results presented here do not include these outlying runs, as there is not yet a full understanding of why they happen in the simulations and they do not appear to be very realistic. Removing these runs avoids the problem, but is very *ad hoc*. A different approach was taken for the same issue in the North Sea haddock MSE (see Figure 4.3), in which case the solution was to limit interannual change in fishing mortality to $\pm 25\%$. Neither of these *ad hoc* fixes are particularly satisfactory, and the issue

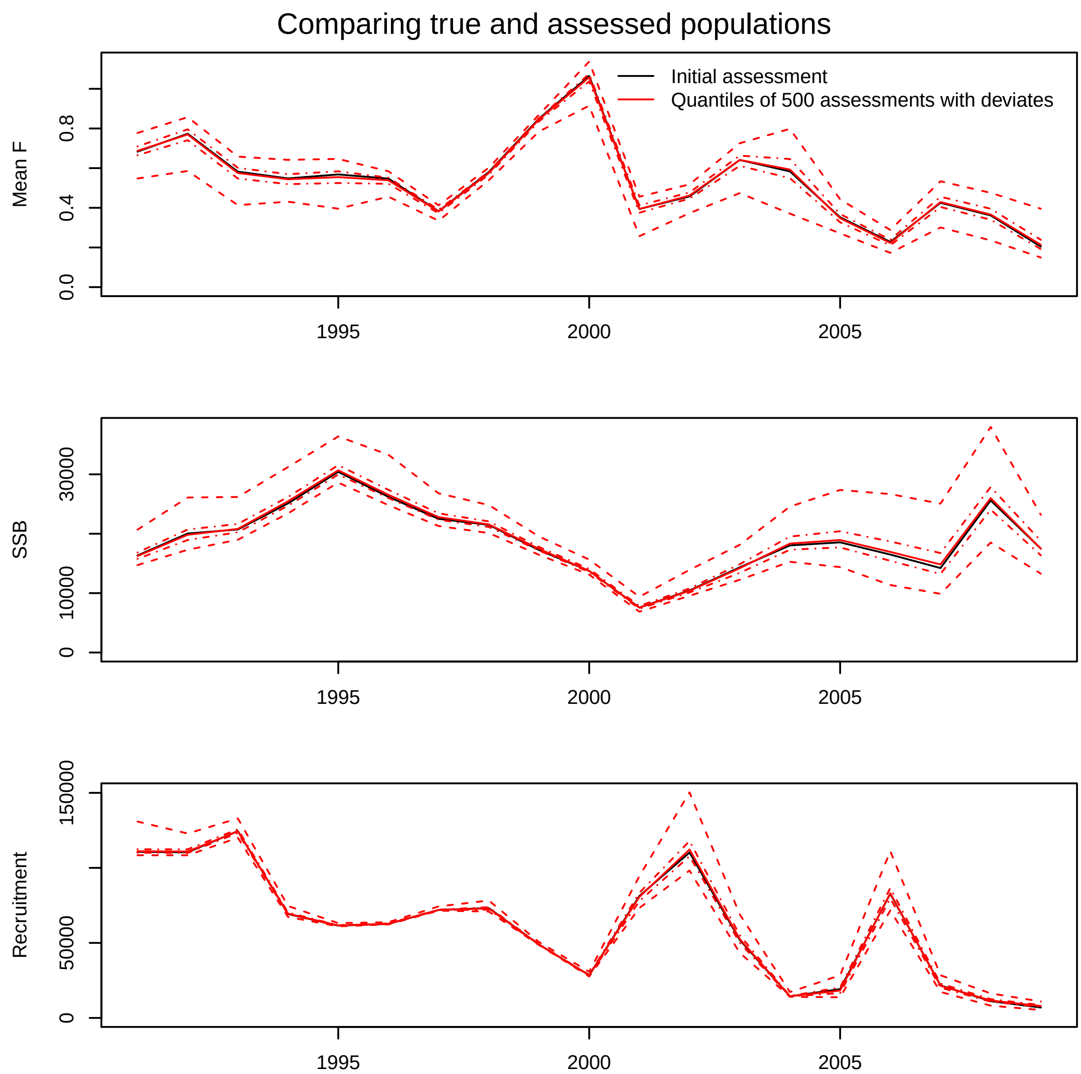


Figure 6.5: Comparison of Rockall haddock summary population values from the standard ("true") assessment (black lines) with those from $K = 500$ iterations including stochastically-generated survey indices (red lines; 5%, 25%, 50%, 75% and 95% quantiles are shown).

needs to be addressed in future work.

6.4 Results

The great advantage of the new FLR implementation used for this MSE is the speed with which each evaluation can be completed. Previous work (Section 4, Chapter VI Needle 2008b) was limited to 50 iterations for each target F, whereas here I have been able to run 500 iterations for each F (and indeed 1000 iterations would have been quite possible). This greatly increases coverage of the range of simulated possibilities, and improves confidence in the conclusions. Two values of target F were considered

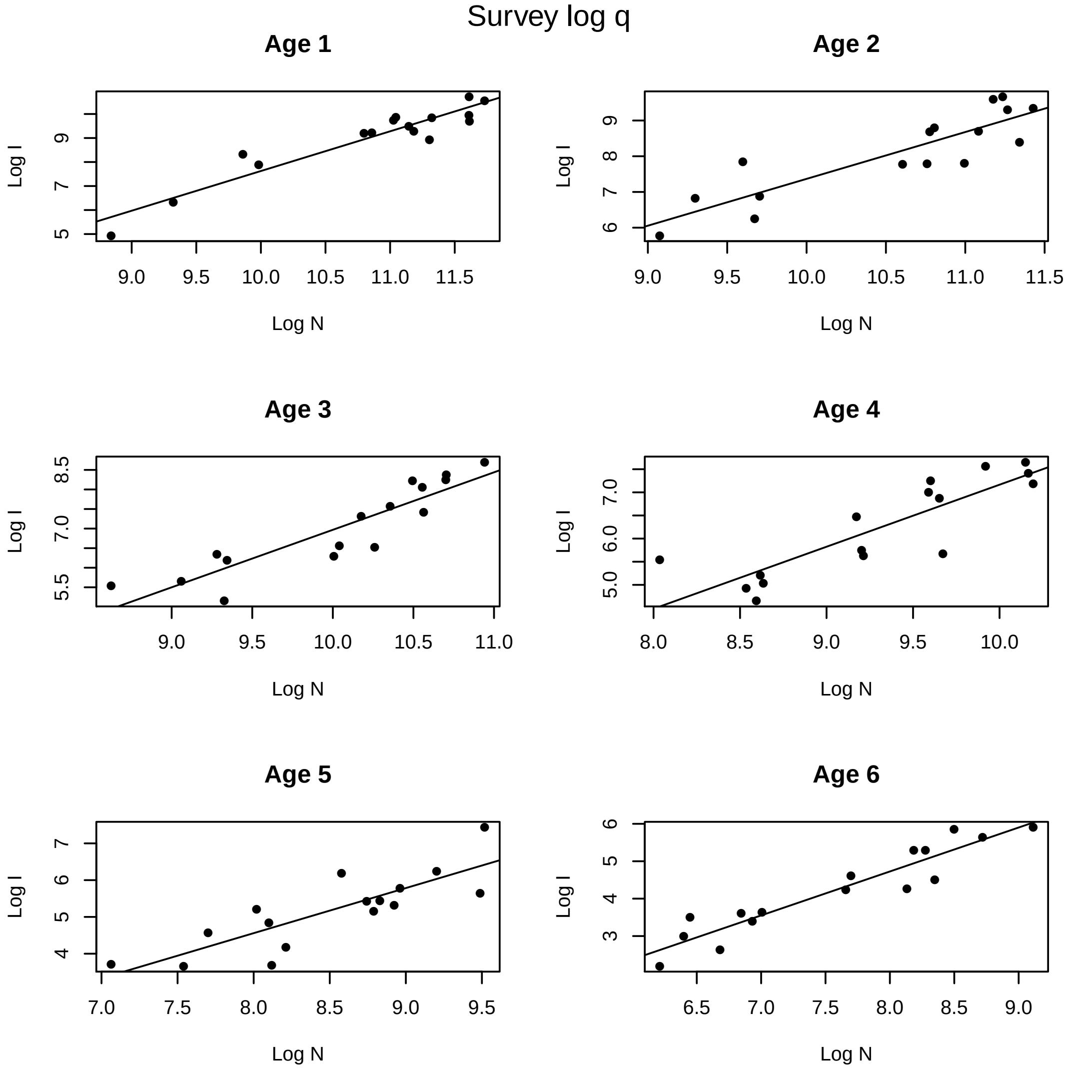


Figure 6.6: Scatterplots (by age) comparing the logged survey indices ($\ln I$) with the logged stock abundance estimates ($\ln N$) from the "true" historical assessment for Rockall haddock. Fitted lines give the best linear relationships (see Equation 6.3).

here, and each iteration was run for 22 years into the future (being a standard 20 year simulation period, with two extra years to allow for quota-setting forecasts in the final simulation year).

Figure 6.7 gives summary plots for one realisation of the simulation for which the target $F = 0.3$ (recall that 500 such realisations were run for each of two target F values considered). Permitted quota follows an overall upwards trajectory with only minor fluctuations, with true landings and discards following suit according to the fixed relationship between them. True (or realised) mean F fluctuates around the target F level (0.3), although the assessed mean F is much closer to the target. The fluctuations are caused by a combination of implementation lag and the TAC constraint (see page 55). Even with these fluctuations, the average F over the simulation period is consistently lower than the historical average. Recruitment remains around an average value in this run. SSB fluctuates in a manner similar (but opposite) to mean F, and for this iteration is always above B_{pa}.

In contrast, Figure 6.8 shows one of the few examples of an iteration for which true mean F hits the maximum value (2.0). Such an extreme discrepancy between true and assessed stock values for mean F and SSB is difficult to interpret, and (as mentioned above) such runs have all been removed from the overall analysis.

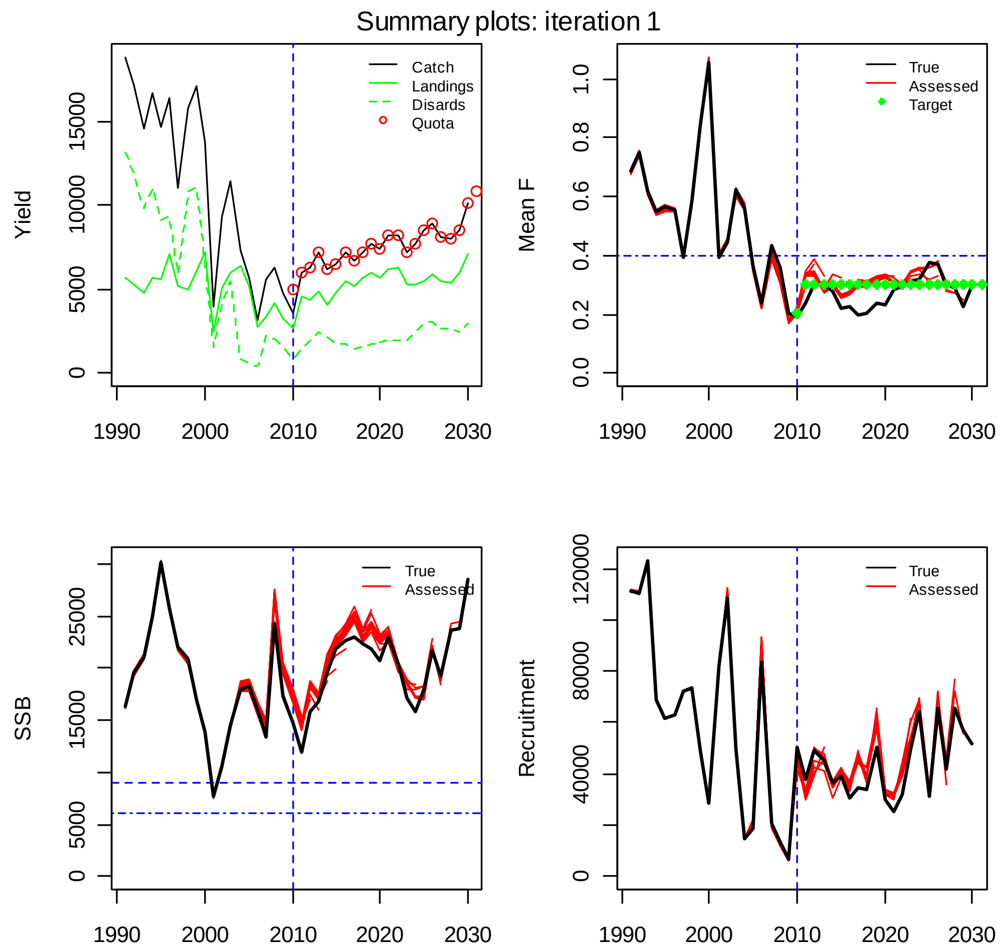


Figure 6.7: Summary plots for iteration 1 of the Rockall haddock MSE. Here the target F is 0.3. For all plots, the vertical blue line denotes the last historical year. Top left: total catch (black solid line), landings (green solid line) and discards (green dashed line). Red circles show the intended TAC for each year. Top right: time series of mean F, with true values in black while the assessed values from each year of the forward simulation are shown in red. Green dots indicate the intended mean F. The horizontal blue line shows the value of F_{pa}. The same colour scheme is used for SSB (bottom left; horizontal lines show B_{pa} and B_{lim}) and recruitment (bottom right).

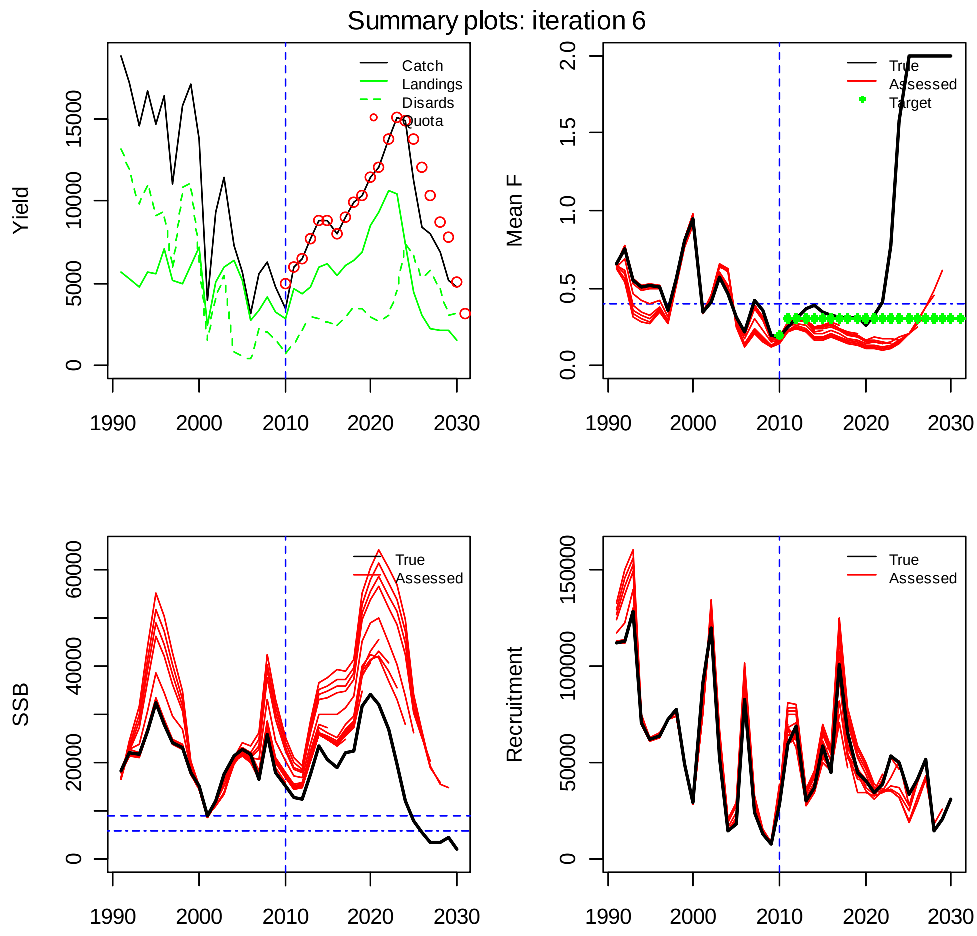


Figure 6.8: Summary plots for iteration 6 of the Rockall haddock MSE. See caption to Figure 6.7 for details.

Staying with the same simulation (target $F = 0.3$), Figure 6.9 summarises all 491 simulation iterations (that is, all 500 iterations minus the 9 runs for which F became equal to 2.0: see above for a discussion). As I have noted before, the median values from these plots are the result of smoothing across different realisations of recruitments, and are therefore only useful as an indication of likely future events. Given this caveat, the simulations indicate that SSB is likely to rise initially before stabilising at or around 25 to 30 kt, mean F is likely to fluctuate considerably around the target level (but should in any case be able to remain low on average), and total catches will rise to a mean level of around 8 kt.

Figure 6.10 provides the same summary information for the run with target $F = 0.4$. Here there were 456 valid runs (91.2% of the total) for which F did not hit 2.0. The yield in these runs is similar to those for which the target $F = 0.3$ (at around 8 kt on

Run	Target F	Num. years $B < B_{\text{pa}}$	Num. years $B < B_{\text{lim}}$
1	0.3	0.17	0.03
2	0.4	1.18	0.28

Table 6.1: Summaries of risk (number of years in each iteration for which biomass is less than reference points, averaged over iterations) for each of the tested levels of the target F. Only valid iterations have been included here (that is, those for which F does not reach 2.0).

average), but at the cost of a lower SSB (generally less than 20 kt). Recruitment is also similar to the previous case. I note that the true mean F for this analysis is much closer to the target F (0.4) than for the previous case (when the target $F = 0.3$).

I summarise *risk* from these simulations as follows. For each value of the target F, I consider each iteration separately, and count the number of years in that iteration for which biomass was less than B_{pa} or B_{lim}. The results of this analysis for both evaluation runs are summarised in Table 6.1, and Figures 6.11 and 6.12. For both levels of the target F, the risk of biomass falling below either biomass reference points is very low. The number of years for which $B < B_{\text{lim}}$ in particular is considerably less than 1.0, for both target F values.

6.5 Conclusions

On the basis of the simulations presented in this Section, it would appear that proposed EU-RF management plan for Rockall haddock is sustainable – that is, the risk of biomass falling below either of the specified reference points over the future 20-year period is very low. As for Sections 4 and 5, however, several caveats should be borne in mind, however, when considering this result.

The evaluation follows the example of the ICES stock assessment in not allowing explicitly for the presence of two fleets with very different characteristics. The simulations are based on an assessment and data which end in 2010, a year in which very few Russian Federation (RF) vessels fished at Rockall (due in part to considerable fishing opportunities in the Barents Sea). The simulations are therefore based on a view of fishery dynamics which is overwhelmingly driven by the characteristics of the EU fleet. Should the RF fleet return to Rockall in significant numbers in the future, this view may not longer pertain. It is possible to model separate fleets in FLR, and this should be considered as a priority in any future revisions.

The evaluation is also limited by the general hindrances that affect all analyses of this type. There is no bioeconomic feedback loop in the simulation, so fishing practices at Rockall (and, importantly, the number of vessels that fish there) are assumed to affect stock dynamics only through the medium of quotas. In reality, increased prices for haddock might increase the number of vessels fishing at Rockall, and thereby have an effect on the risk estimates outlined in this paper - increased fuel costs could have the opposite effect. The proportions discarded-at-age are assumed to be fixed through time (and these are in any case generally extrapolations from the North Sea). Finally, the lack of a multispecies component to the analysis could (for some mixed-fishery vessels, at least) leads to difficulty in drawing firm conclusions.

Without consideration of aspects such as different fleet characteristics and spatial responses to closed areas (for example), this case study doesn't lead directly to new insights about the affect of fleet dynamics (fishermen's choices) on management strategy evaluations. However, it does demonstrate succinctly that evaluations with 500 or 1000 iterations are certainly possible. Runs with many iterations in these analyses are preferable to runs with fewer, as the former allow for a more complete exploration of the full uncertainty range: and hence a more robust analysis.

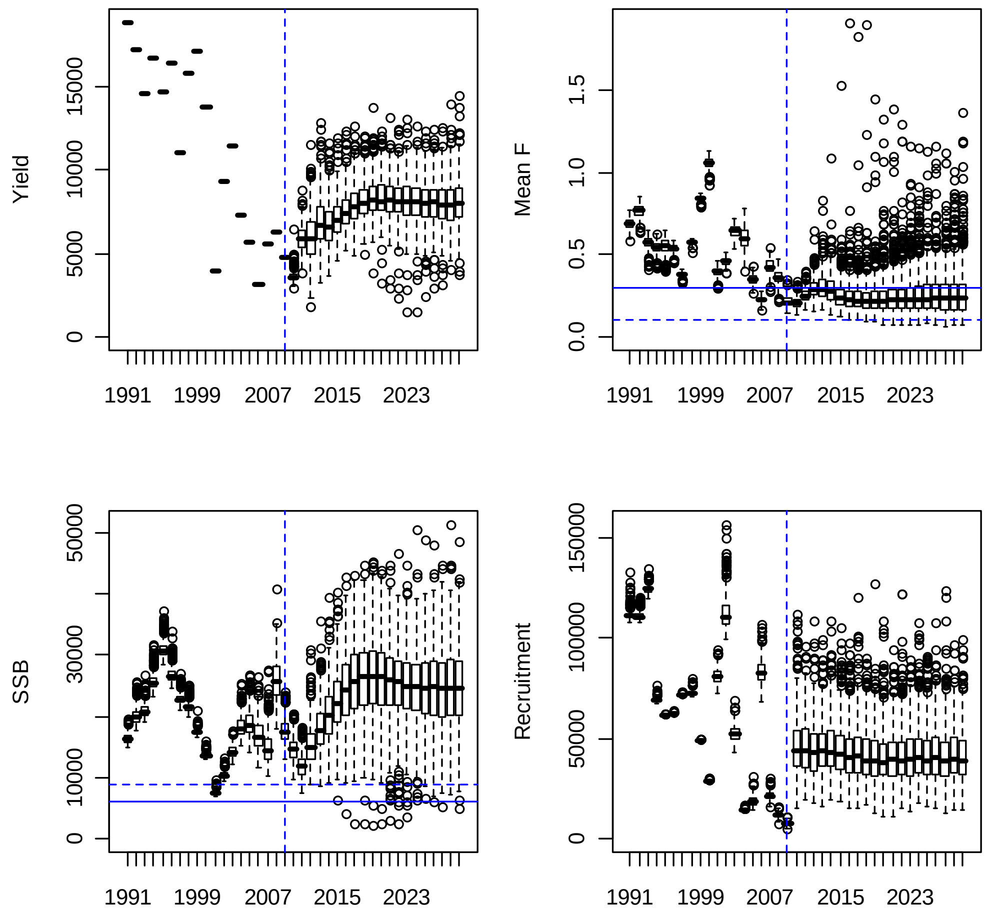


Figure 6.9: Summary plots true population values from the 491 valid simulation iterations (that is, all those without F reaching 2.0), with target $F = 0.3$. The short horizontal lines indicate the medians, and the boxes the quartiles (25%ile and 75%ile). The lower whisker gives the value of 25%ile $-$ (1.5 $\times$ (75%ile $-$ 25%ile)) and the upper gives 75%ile $+$ (1.5 $\times$ (75%ile $-$ 25%ile)). Outliers beyond this range are shown by open circles. The lines on the top-right plot show the target F (upper) and $F = 0.1$ (lower), while those on the bottom-left plot show B_{pa} (upper) and B_{lim} (lower). Vertical dashed blue lines show the last historical year.

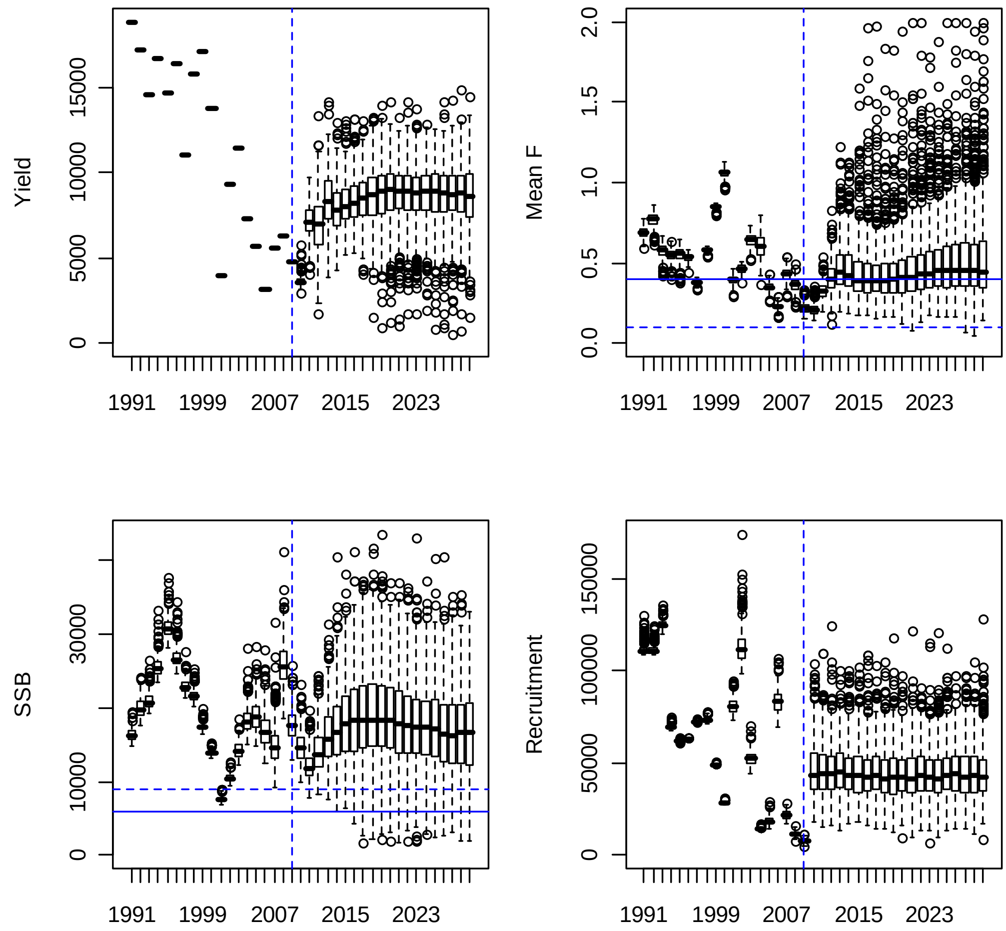


Figure 6.10: Summary plots true population values from the 456 valid simulation iterations (that is, all those without F reaching 2.0), with target $F = 0.4$. The short horizontal lines indicate the medians, and the boxes the quartiles (25%ile and 75%ile). The lower whisker gives the value of $25\%\text{ile} - (1.5 \times (75\%\text{ile} - 25\%\text{ile}))$ and the upper gives $75\%\text{ile} + (1.5 \times (75\%\text{ile} - 25\%\text{ile}))$. Outliers beyond this range are shown by open circles. The lines on the top-right plot show the target F (upper) and $F = 0.1$ (lower), while those on the bottom-left plot show B_{pa} (upper) and B_{lim} (lower). Vertical dashed blue lines show the last historical year.

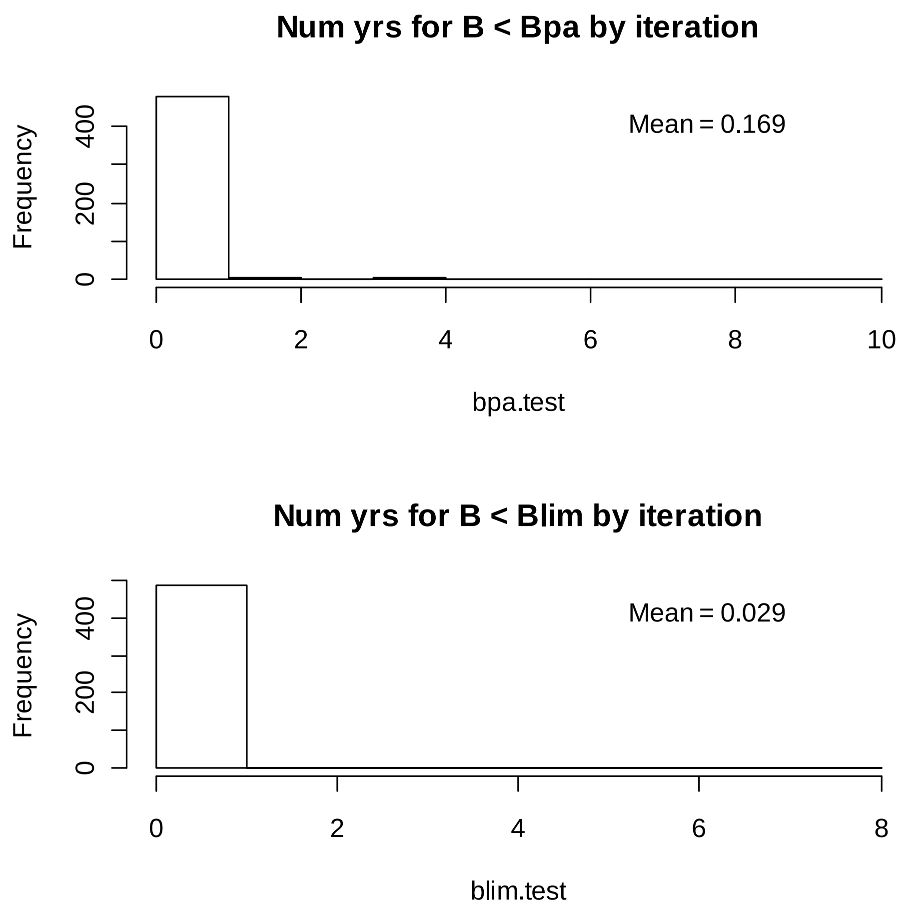


Figure 6.11: Histograms of the number of years within each iteration (target $F = 0.3$, 491 valid runs only) in which SSB $B < B_{\text{pa}}$ (upper) or $B < B_{\text{lim}}$ (lower). The average number of years (out of a maximum total of 20) is given for each case.

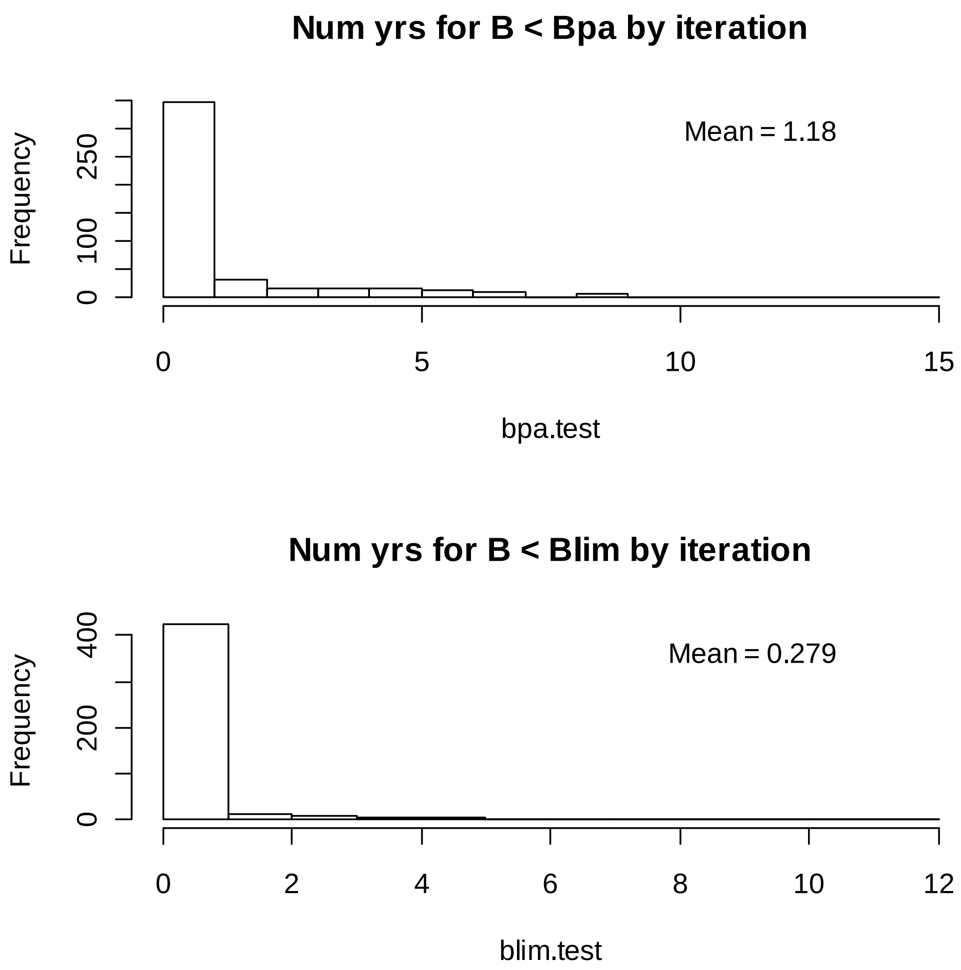


Figure 6.12: Histograms of the number of years within each iteration (target $F = 0.4$, 456 valid runs only) in which SSB $B < B_{\text{pa}}$ (upper) or $B < B_{\text{lim}}$ (lower). The average number of years (out of a maximum total of 20) is given for each case.

7 Quota points

7.1 Background

In many parts of the world, serious consideration is being paid by fisheries managers to alternative methods of managing their fisheries. Although implemented with the best of intentions, many management paradigms have demonstrably failed to provide sustainability in target fisheries, with the result that many of the world's fish stocks are thought to be overexploited (although see Branch et al. 2011). Common examples of extant management instruments include landings quota (often referred to incorrectly as TAC, or Total Allowable Catch), restrictions on fishing effort through days-at-sea limits, gear regulations, and many others (Pitcher et al. 1998, Kruse et al. 2005, Motos and Wilson 2006).

The North Sea cod stock is managed via a combination of landings quotas, effort restrictions and gear measures (ICES 2011c). Even with stringent effort controls, it is likely that any specified quota for North Sea cod will control landings only, not mortality. If overquota cod cannot be landed due to such policy instruments as the UK Buyers and Sellers regulation (Scottish Government 2005), they will be discarded dead at sea. To a certain extent, skippers are able to avoid cod areas, but accidental catches will inevitably occur (ICES 2011c). In fact, when the prevailing management structure is applied to a mixed fishery such as the North Sea, it is hard to imagine how an outcome other than discarding could be possible. The recovery of the cod stock from recent low levels in this situation is not impossible, but it is much less likely. Landings quotas *cannot* be synchronised with the species mix that skippers encounter in different areas and at different times – it is a functional impossibility, and leads to many of the problems fisheries managers face today (Murawski and Finn 1988). Many writers have concluded that a set of single-species quotas is an inappropriate management system that is unlikely to be sustainable (for example, see references in Villasante et al. 2011)

However, it is not possible to simply ban discards and leave the rest of the existing management structure unaltered. Vessels would inevitably run out of quota for one species more quickly than for other species, and a simple discard ban would prevent many vessels going to sea at all for long periods of the year and would result in the *de facto* closure of much of the fishery. It is certainly preferable to encourage the industry to avoid catching cod, rather than punish them on the occasions when they do so. One plausible way of doing this (at least in theory) is the following *quota points* scheme, taken from a recent discussion paper (Needle 2007b):

- A general multi-species quota is determined for each relevant area, not in terms of tonnes but *points*.

- The points are allocated to countries and thence to individual skippers in a manner analogous to what is done now with tonnes. Each skipper now knows how many points he (or she) has to spend in the coming year.

- The fleet begins to fish. There are no species-specific quotas, effort limitations or gear technical measures in this version of the scheme. Crucially, there are no discards allowed – everything that is caught must be landed and reported. The discard ban operating in Norway is accompanied by several other management measures, but it may be that these were introduced to ease the passage of the fishery into a no-discard regime and might not be absolute requirements (Graham et al. 2007).

- The main new element is that, when landing and reporting, the skipper must now add up the number of points that his catch represents, and deduct that from his total for the year. Different species would be worth different points, so (for the sake of argument) one tonne of cod could be 10 points, one tonne of haddock 5 points, and one tonne of whiting 2 points: there would need to be considerable thought put into this points scale. Once the vessel is out of points, that is it for the year, although points could be transferrable (and could therefore be bought and sold or leased, much as quota is now).

In quantitative terms, the calculations required for such a scheme could operate as follows:

1. Estimate time-series of maximum sustainable yield values F_{msy} and B_{msy} for each stock (see references in Pilling et al. 2008).

2. Calculate a *threat index*

$$T = \ln\left(\frac{F_{\text{msy}}}{F_{\text{sq}}} \times \frac{B_{\text{current}}}{B_{\text{msy}}}\right). \tag{7.1}$$

   Thus $T \geq 0$ indicates a stock in reasonable health, while $T < 0$ suggests a threatened stock.

3. Estimate the current total catch (landings plus discards, in tonnes) per country per stock, averaged over the last three historical years. Multiply these catches by the threat index, and sum across stocks. This is the total number of available points.

4. The allocation of points per country should be based on the current allocation key, but will of course be open to considerable negotiation.

5. As a further development, it should be possible to use cumulative sum approaches to determine time periods covered by different recruitment regimes (ICES 2009a). Then estimates such as F_{msy} could be generated for the most recent recruitment-regime period only, thus avoiding problems associated with the use of historical time-periods when some stocks were (apparently) more productive (Cook and Heath 2005).

I note here that a similar scheme has been suggested independently (although subsequently) by ClientEarth and Marine Conservation Society (2009, known as *fishing credits*), and (at the time of writing) the approach was being considered seriously by Scottish Government fisheries managers as a strong alternative to single-species quotas (in that context it is referred to as *multispecies catch quotas*). The revised Common Fisheries Policy (CFP) proposed by the European Commission in July 2011 (European Commission 2011) calls for discard bans and catch quotas, although without clearly specifying how these would operate in practice. Suggestions have been put forward by Schou (2011) and Holm and Schou (2011), and there has been a scoping study of the effect of a potential ban on English vessels (Catchpole et al. 2011), but rigorous evaluation is lacking as yet.

7.2 Issues with quota points

The advantages of this scheme are as follows:

- The industry would become effectively self-regulating. Skippers could by all means go fishing for cod (or any other species with a high points value), but they would run out of points very quickly in so doing. There would be a strong incentive to a) look for areas low in high-points species, and move from these areas if found; b) use gear that avoided catching high-points species; and c) space out fishing effort through the year so as to ensure their points lasted.

- If skippers did accidentally catch cod while fishing for something else, they could land it without recrimination (except for losing points). The fish, which are dead once caught anyway, would therefore not be wasted.

- The scheme is very simple, once the points are estimated, and reduces enormously the number of regulations that the industry has to be concerned with.

Some of the disadvantages are:

- It will be difficult to ensure that there is no discarding. If this cannot be guaranteed, then the scheme is unlikely to work. On the other hand, while discarding remains, cod recovery is far less likely. Recent trials in Denmark and Scotland (Marine Scotland 2010, Kindt-Larsen et al. 2011) of CCTV-based monitoring schemes (see also Section 12.3) would suggest that a discard ban could be a tractable solution in the near future.

- The scheme would be difficult to set up in the first place, although the example given above could indicate a way forward. The methodology would have to be agreed for turning the various single-species and multi-species stock assessments into a final quota-points number for a particular area, and the allocation of these points to different countries and stakeholders would be a source of contention. The specification of the points value of each species would also require much careful analysis.

- If boats must land everything they catch, then there will be large landings of previously non-commercial species such as gurnards and dabs. This may not be a bad thing, as it maximises the efficient use of the resource, but it would require the development of markets for previously unmarketed fish – or processes to utilise such fish in other ways. It would also remove biomass from the marine ecosystem that would otherwise have been returned as discards (Zhou 2008).

However, the main problem, and the one which motivates this thesis, is that managers have no way of telling whether a quota-points scheme will improve management of their fisheries, or do the opposite. What would be the response of the fishing industry to such radical change? Would improved stock sustainability for North Sea cod be the result, and if so, at what cost to other species? Would some parts of the industry be disadvantaged compared to others? Discussions of this kind cannot begin until more is known about fleet dynamics in such situations. The management approach cannot be evaluated until a simulation framework is developed that characterises these dynamics. I will return to this consideration in Chapter IV.

8 Survey-based assessment models

8.1 Background

Stock assessments based on research-vessel surveys or other fishery-independent sources of information are becoming increasingly important as drivers of fisheries management advice, in Europe and elsewhere. In some cases this approach has arisen as a consequence of stringent management measures which have led to less reliable commercial catch and effort data; in others, the stock trends indicated by fishery-independent data are used as informative counterparts to more traditional catch-based assessment methods. Examples of such methods include catch-size analyses (CSA; Mesnil 2003), biomass random-effect models (BREM; Trenkel 2007), year-class curves (YCC; Cotter et al. 2007), extensions to time-series analysis (TSA; Gudmundsson 1994), and length- (Dobby 2005) or age-based separable survey-based models (SURBA; Needle 2003, Needle 2004a, Beare et al. 2005, Mesnil et al. 2009).

The basis of SURBA is a simple survey-based separable model of mortality. This was first applied to European research-vessel survey data by Cook (1997), but the underlying model has a long history in catch-based fisheries stock assessment (e.g. Fournier and Archibald 1982, Pope and Shepherd 1982, Deriso et al. 1985, Gudmundsson 1986, Johnson and Quinn II 1987, Patterson and Melvin 1996): see Quinn II and Deriso (1999) for a summary.

Cook (1997) took existing separable methods and developed a way to apply them to survey data alone; all existing approaches had been based on catch data, or a combination of catch and survey data. Cook called his implementation RCRV1A, and used it to estimate population trends for a number of European stocks. However, the program was not made generally available, and its use didn't extend much past the original paper and a follow-up (Cook 2004).

During preparation for the ICES Northern Shelf assessment working group in Copenhagen in 2002 (ICES 2002), it became clear that population signals arising from catch and survey sources were quite different, particularly for gadoid stocks in the West of Scotland and Irish Sea (ICES Divisions VIa and VIIa). This was evident from trends in survey residuals from catch-based assessments, but it was not obvious what the population trends would be if based on the surveys alone. To address this, I developed an updated version of Cook's model, restructured in Fortran 90 (although as yet without a Windows interface, and using only one survey at a time). This was SURBA version 1.0, which became SURBA version 1.03 during the ICES meeting (Appendix 1 in ICES 2002). The implementation was rough and ready, but the results appeared to concur with the group's prior perceptions. Version 1.03 subsequently became the basis of a paper on survey-based analysis for haddock in Division VIa (Beare et al. 2002, Beare et al. 2005).

SURBA (version 3.0; see also ICES 2010c) is used for two main purposes in ICES assessment working groups: to supplement existing catch-based VPA-type analyses, and to provide the basis for advice for a number of stocks for which catch data are not thought to be reliable. Among other improvements, SURBA 3.0 features a Windows interface, and is able to model data from several surveys. It is used very widely to provide advice for stocks in the Mediterranean Sea and elsewhere, for which data are not available for standard catch-at-age assessments (see, for example: Ungaro et al. 2008, GFCM-SAC 2008, STECF 2010). Pomarede et al. (2006) used the model in an MSE context to evaluate the comparative utility of advice based on fishery-dependent and fishery-independent data for North Sea herring. An implementation of the SURBA method in the SAS framework has been used in Canada to assess the status of stocks for which there are fishery moratoria and hence no catch data (Cadigan 2010).

The most recent development is SURBAR (that is, SURBA in R: see Section 9.2 in ICES 2009a, and below) which features improved uncertainty estimation and a new parameter-estimation algorithm that avoids the use of NAG library routines (Numerical Algorithms Group 2002), the dissemination of which is restricted by copyright issues.

8.2 PROBLEMS WITH SURVEY-BASED ASSESSMENTS

SURBA has been subjected to methodological testing on a number of occasions (ICES 2004, ICES 2006c, Mesnil et al. 2009, Needle 2004c, Needle 2004b). However, all such tests have been based on simulated data from virtual populations, generated by simple simulation models (e.g. NRC 1998, Needle 2008d) which make correspondingly simple assumptions about the relationship between the survey index I and stock abundance N (often using $I = qN$ where q is catchability). In reality, survey stations are sparsely distributed, and q may vary considerably from year to year depending on whether (for example) the survey hits a spawning aggregation or not. When simulating a survey, therefore, it is important to characterise this spatial dependency, and this is often not done adequately.

This problem causes subsequent difficulties with management strategy evaluations. As discussed above (page 88), problems with the reliability of catch data have led many managers to consider the possibility of basing management decisions on survey data alone. Indeed, this has already been done for stocks like Division VIa haddock (see Section 5). In order to evaluate the likely success of any such approach, a framework is required within which the implications can be ascertained appropriately. Current approaches will not consider the spatial and catchability aspects of a survey in simulating survey data, and so may result in conclusions about survey-based management that are misleading. Hence, any evaluation of a survey-based management approach should be carried out using a spatial simulation model that can account for the specific issues of survey-based assessment methods, and this is the motivation for discussing survey-based assessment issues in this thesis. In the remainder of this Section, I consider the SURBA method itself (along with the SURBAR implementation), and present brief results of the application of SURBAR to North Sea haddock data.

8.3 SURBA 3.0 AND SURBAR

Much of this Section is derived from a course I gave at DFO North-West Atlantic Fisheries Centre, St. John's, Newfoundland, Canada, during 3-4 September 2008 (Needle 2008e), with additional material pertaining to the new SURBAR implementation. I include it here for completeness, given the potential relevance of the method to evaluations of survey-based management (when considered within a spatial simulation framework).

8.3.1 Basis

The separable model used in SURBA assumes that total mortality $Z_{a,y}$ for age a and year y can be expressed as

$$Z_{a,y} = s_a \times f_y, \tag{8.1}$$

where s_a and f_y are respectively the *age* and *year* effects of mortality (see also Table 8.1). Note that this differs from the usual assumption in that total mortality Z is the quantity of interest, rather than fishing mortality F. Then, given $Z_{a,y}$, abundance $N_{a,y}$ can be derived as

$$\begin{aligned} N_{a,y} &= N_{a_0,yc_0} \exp\left(-\sum_{m=a_0}^{a-1}\sum_{n=y_0}^{y-1} Z_{m,n}\right) \\ &= r_{yc_0} \exp\left(-\sum_{m=a_0}^{a-1}\sum_{n=y_0}^{y-1} Z_{m,n}\right) \end{aligned} \tag{8.2}$$

where a_0 and $yc_0 = y - a - a_0$ are respectively the age and year in which the fish measured as $N_{a,y}$ first recruit to the observed population (y_0 is the first year of the dataset). Thus the abundance at each age and year of a cohort is given by the recruiting abundance (denoted by $r_{yc_0} = N_{a_0,yc_0}$) of the relevant cohort modified by the cumulative effect of mortality during its lifetime (Table 8.2).

	f_{06}	f_{07}	f_{08}
s_1	$Z_{1,06} = s_1 \times f_{06}$	$Z_{1,07} = s_1 \times f_{07}$	$Z_{1,08} = s_1 \times f_{08}$
s_2	$Z_{2,06} = s_2 \times f_{06}$	$Z_{2,07} = s_2 \times f_{07}$	$Z_{2,08} = s_2 \times f_{08}$
s_3	$Z_{3,06} = s_3 \times f_{06}$	$Z_{3,07} = s_3 \times f_{07}$	$Z_{3,08} = s_3 \times f_{08}$

Table 8.1: An example of the separable model for mortality Z used in SURBA.

	2006	2007	2008
Age 1	$N_{1,06} = r_{05}$		
Age 2		$N_{2,07} = N_{1,06}\mathrm{e}^{-Z_{1,06}} = r_{05}\mathrm{e}^{-s_1 f_{06}}$	
Age 3			$N_{3,08} = N_{2,07}\mathrm{e}^{-Z_{2,07}} = r_{05}\mathrm{e}^{-s_1 f_{06} - s_2 f_{07}}$

Table 8.2: SURBA Derivation of abundance N using age effects $\mathbf{s}$, year effects $\mathbf{f}$ and cohort effects $\mathbf{r}$. Only a single cohort is shown here. Note that r_{05} refers to the abundance at the recruiting age of the 2005 year-class (which recruited at age 1 in 2006).

8.3.2 Estimation

The parameters to be estimated when fitting the model are $\Theta = [\mathbf{s}, \mathbf{f}, \mathbf{r}]$, where:

$$\begin{aligned}
\text{Age effects} &: \quad \mathbf{s} = [s_a] = [s_{a_0}, s_{a_0+1}, \ldots, s_A] \\
\text{Year effects} &: \quad \mathbf{f} = [f_y] = \left[f_{y_0}, f_{y_0+1}, \ldots, f_Y\right] \\
\text{Cohort effects} &: \quad \mathbf{r} = [r_{yc}] = \left[r_{y_0-A+a_0}, r_{y_0-A+a_0+1}, \ldots, r_{Y-a_0}\right]
\end{aligned}$$

Here A is the oldest age and Y is the last year in the dataset. The data available may include:

$$\begin{array}{rcl}
\text{Age-structured abundance indices} & : & \mathbf{I} = [I_{a,y,i}] \\
\text{Biomass abundance indices} & : & \mathbf{J} = \left[J_{y,j}\right] \\
\text{Stock weights-at-age} & : & \mathbf{W} = [W_{a,y}] \\
\text{Proportion mature-at-age} & : & \mathbf{Mat} = [\mathrm{Mat}_{a,y}] \\
\text{Proportion mortality before spawning} & : & \mathbf{PZ} = [\mathrm{PZ}_{a,y}] \\
\text{Age-structured index catchabilities} & : & \mathbf{q} = [q_{a,y,i}] \\
\text{Age-structure index weightings} & : & \omega = [\omega_{a,y,i}] \\
\text{Age-structured index timings} & : & \rho = [\rho_i] \\
\text{Biomass index weightings} & : & \nu = \left[\nu_{y,j}\right] \\
\text{Penalty term weighting (smoothing parameter)} & : & \lambda
\end{array}$$

Here $i \in [1,2,\ldots,NI]$ indexes age-structured series, while $j \in [1,2,\ldots,NJ]$ indexes biomass (non-age-structured) series. SURBA assumes that at least one age-structured survey index is available: biomass indices are optional. If present, it is assumed that biomass indices are measured at spawning time, following the convention used in such models as ICA (Patterson and Melvin 1996).

The fitting procedure is as follows. Abundance indices (age-structured and biomass) are mean-standardised using

$$\begin{aligned}
I'_{a,y,i} &= I_{a,y,i}\left(\frac{1}{(A-a_0+1)(Y-y_0+1)}\sum_{m=a_0}^{A}\sum_{n=y_0}^{Y} I_{m,n,i}\right)^{-1}, && (8.3)\\
J'_{y,j} &= J_{y,j}\left(\frac{1}{Y-y_0+1}\sum_{n=y_0}^{Y} J_{n,j}\right)^{-1}, && (8.4)
\end{aligned}$$

so that the mean of each index over all ages and years is 1.0. Given estimated parameters $\hat{\mathbf{s}}$, $\hat{\mathbf{f}}$ and $\hat{\mathbf{r}}$, fitted age-structured abundance indices are calculated using

$$\hat{Z}_{a,y} = \hat{s}_a \hat{f}_y \tag{8.5}$$

and

$$\hat{N}_{a,y} = \hat{r}_{y_0-a-a_0} \exp\left(-\sum_{m=a_0}^{a-1}\sum_{n=y_0}^{y-1} \hat{Z}_{m,n}\right) \tag{8.6}$$

and

$$\hat{I}'_{a,y,i} = q_{a,y,i}\hat{N}_{a,y}. \tag{8.7}$$

Here $q_{a,y,i}$ denotes the relative *catchability* of survey i for fish aged a in year y. It is very difficult to estimate $q_{a,y,i}$, and in extant applications it has usually been fixed to 1.0 for all a, y, and i (although see, for example, Cadigan 2010). However, it can be shown that while fluctuations in catch curves (that is, plots of $\ln\hat{N}_{a,y}$ by cohort) are caused by changes in Z or q, positive slopes in catch curves can only be due to q (as Z cannot be negative in reality, assuming a closed population). It is possible, therefore, that catch curves could be used to compute a *lower bound* on catchability q, although this has yet to be investigated in any detail. Work is also proceeding in Canada on methods to estimate catchability using survey data by linking the stock assessment closely with the survey design itself (Noel Cadigan, DFO, St. John's, *pers comm*).

Note that both $\hat{I}'_{a,y,i}$ and $\hat{N}_{a,y}$ refer to the stock as measured at January 1 of the year in question. In order to compare these fitted values with observations, SURBA backshifts the observed indices from the time of observation to the start of the year (January 1st), thus:

$$I'^{*}_{a,y,i} = I'_{a,y,i}\exp\left(\rho_i\hat{Z}_{a,y}\right), \tag{8.8}$$

where ρ_i is the decimal time of year at which the ith survey takes place (so that, for example, $\rho = 0.5$ for a survey that starts on July 1st). Then the sum-of-squares to be minimised for NI age-structured indices is

$$\mathrm{SSQ}_I = \sum_{i=1}^{\mathrm{NI}}\sum_{a=a_0}^{A}\sum_{y=y_0}^{Y}\omega_{a,y,i}\left(\ln I'^{*}_{a,y,i} - \ln\hat{I}'_{a,y,i}\right)^2. \tag{8.9}$$

The procedure for biomass indices is somewhat different. Since these indices refer to all mature fish, there is no sensible way to shift a biomass index back to the start of the year on the basis of age-structured mortality up until the time of the survey. Rather than shifting biomass indices back, SURBA shifts SSB estimates forward to the time of the survey (assumed to be spawning time) before comparing observations with fits. Forward-shifted SSB is estimated as

$$\hat{B}_y = \sum_{a=a_0}^{A}\hat{N}_{a,y}W_{a,y}\mathrm{Mat}_{a,y}\exp\left(-\mathrm{PZ}_{a,y}\hat{Z}_{a,y}\right), \tag{8.10}$$

and the fitted biomass indices are then

$$\hat{J}'_{y,j} = q_{y,j}\hat{B}_y^{k_j} \tag{8.11}$$

where k_j is the power relationship for the biomass index (currently it is assumed that $\mathbf{k} \equiv \mathbf{1}$). The sum-of-squares to be mimimised for NJ biomass indices can then be written as

$$\mathrm{SSQ}_J = \sum_{b=1}^{NJ} \sum_{y=y_0}^{Y} v_{y,j} \left(\ln J'_{y,j} - \ln \hat{J}'_{y,j} \right)^2. \tag{8.12}$$

The final element of the sum-of-squares is a term which penalises inter-annual variation in the estimated year-effect $\hat{\mathbf{f}}$ (Cook 1997), and which is defined as

$$\mathrm{SSQ}_\lambda = \lambda \sum_{y=y_0}^{Y-2} \left(\hat{f}_y - \hat{f}_{y+1} \right)^2. \tag{8.13}$$

Here λ is a smoothing factor which has no intrinsic justification and for which there is no estimation methodology: the user is expected either to experiment with different values of λ and select that which provides appropriate variation in $\hat{\mathbf{f}}$, or to leave the default value ($\lambda = 1.0$) unchanged. Then the overall sum-of-squares to be minimised is

$$\mathrm{SSQ} = \mathrm{SSQ}_I + \mathrm{SSQ}_J + \mathrm{SSQ}_\lambda \tag{8.14}$$

Fixed values

As presented above, the SURBA model is indeterminate and has no unique solution. For this reason, elements of $\mathbf{s}$ and $\mathbf{f}$ must be fixed beforehand. If A is the oldest age, Y is the last year, and a_r is a reference age chosen by the user, then the following parameter values are derived from other parameters (and are therefore not directly estimated):

$$s_{a_r} = 1.0 \tag{8.15}$$

$$s_A = \hat{s}_{A-1} \tag{8.16}$$

$$f_Y = \frac{1}{3} \sum_{y=Y-3}^{Y-1} \hat{f}_y \tag{8.17}$$

Uncertainty

SURBA estimates a variance-covariance matrix for the estimated parameters $\hat{\Theta}$. However, the variance and associated confidence limits of derived estimated population characteristics such as mortality $\hat{Z}_{a,y}$, abundance $\hat{N}_{a,y}$ and SSB $\hat{B}_y$ are more directly relevant to users. To generate derived variances, SURBA (version 3.0) uses the delta method (e.g. Seber 1982, Oehlert 1992).

From above, we have seen that the SURBA model has a number of parameters, namely **s**, **f** and **r**, and that the parameter vector for the model is denoted by

$$\begin{aligned}\Theta &= [\mathbf{s}, \mathbf{f}, \mathbf{r}] \\ &= \left[s_{a_0}, \ldots, s_A, f_{y_0}, \ldots, f_Y, r_{y_0-A+a_0}, r_{y_0-A+a_0+1}, \ldots, r_{Y-a_0}\right]\end{aligned}$$

Denote further the estimated variance-covariance matrix of the estimated parameters by $\hat{\text{Var}}\left[\hat{\Theta}\right]$, and let $\mathbf{G}$ denote the transformation to the required model output $\hat{\Phi}$ (which could be mortality or SSB, for example). Further, let $\delta\mathbf{G}$ be the matrix of partial derivatives of $\mathbf{G}$ with respect to the estimated parameters. The delta method then uses a first-order Taylor expansion to approximate the variance-covariance matrix of $\hat{\Phi}$ via

$$\hat{\text{Var}}[\hat{\Phi}] = \hat{\text{Var}}\left[\mathbf{G}(\hat{\Theta})\right] = \delta\mathbf{G}(\hat{\Theta})\hat{\text{Var}}\left[\hat{\Theta}\right]\delta\mathbf{G}(\hat{\Theta})^T.$$

This approximation will be close in general if the assumption of lognormally-distributed errors is reasonably accurate: otherwise, it may be misleading. Standard errors for the components of $\hat{\Phi}$ are obtained by taking square roots of the diagonal elements of this matrix. The estimated parameter correlation matrix $\hat{\text{Corr}}[\hat{\Phi}]$ may also be informative, and is derived from the variance-covariance matrix using

$$\hat{\text{Corr}}[\hat{\Phi}_i, \hat{\Phi}_j] = \frac{\hat{\text{Cov}}\left[\hat{\Phi}_i, \hat{\Phi}_j\right]}{\sqrt{\hat{\text{Var}}\left[\hat{\Phi}_i\right]\hat{\text{Var}}\left[\hat{\Phi}_j\right]}}.$$

Inferred variance estimates

Here I give examples of the calculations required to infer (via the delta method) the variances of population summary statistics and other values produced by SURBA. Note that hats (ˆ) have been dropped throughout for clarity. As a first example, consider mortality $Z_{a,y}$ in age a and year y, where

$$\Phi|_{a,y} = \mathbf{G}(\Theta)|_{a,y} = Z_{a,y} = s_a f_y.$$

Then

$$\delta\mathbf{G}(\Theta)|_{a,y} = \left[\begin{array}{cc}\frac{\delta Z_{a,y}}{\delta s_a} & \frac{\delta Z_{a,y}}{\delta f_y}\end{array}\right] = \left[\begin{array}{cc} f_y & s_a\end{array}\right]$$

and

$$\text{Var}\left[Z_{a,y}\right] = \left[\begin{array}{cc} f_y & s_a\end{array}\right]\left[\begin{array}{cc}\text{Var}\left[s_a\right] & \text{Cov}\left(s_a, f_y\right) \\ \text{Cov}\left(s_a, f_y\right) & \text{Var}\left[f_y\right]\end{array}\right]\left[\begin{array}{c} f_y \\ s_a\end{array}\right]$$

so that

$$\text{Var}\left[Z_{a,y}\right] = f_y^2\text{Var}\left[s_a\right] + 2s_a f_y\text{Cov}\left(s_a, f_y\right) + s_a^2\text{Var}\left[f_y\right].$$

As a second example, consider abundance $N_{2,y}$ at age 2 in year y, which can be written as

$$\Phi|_{2,y} = \mathbf{G}(\Theta)|_{2,y} = N_{2,y} = r_{y-1-a_0} e^{-s_1 f_{y-1}}$$

Then

$$\begin{aligned}\delta \mathbf{G}(\Theta)|_{2,y} &= \begin{bmatrix} \frac{\delta N_{2,y}}{\delta r_{y-1-a_0}} & \frac{\delta N_{2,y}}{\delta s_1} & \frac{\delta N_{2,y}}{\delta f_{y-1}} \end{bmatrix} \\ &= \begin{bmatrix} e^{-s_1 f_{y-1}} & -r_{y-1-a_0} e^{-s_1 f_{y-1}} & -r_{y-1-a_0} e^{-s_1 f_{y-1}} \end{bmatrix}\end{aligned}$$

and

$$\mathrm{Var}\left[N_{2,y}\right] = \begin{bmatrix} e^{-s_1 f_{y-1}} & -r_{y-1-a_0} e^{-s_1 f_{y-1}} & -r_{y-1-a_0} e^{-s_1 f_{y-1}} \end{bmatrix} \times$$
$$\begin{bmatrix} \mathrm{Var}[r] & \mathrm{Cov}(r, s_1) & \mathrm{Cov}\left(r, f_{y-1}\right) \\ \mathrm{Cov}(r, s_1) & \mathrm{Var}[s_1] & \mathrm{Cov}\left(s_1, f_{y-1}\right) \\ \mathrm{Cov}\left(r, f_{y-1}\right) & \mathrm{Cov}\left(s_1, f_{y-1}\right) & \mathrm{Var}\left[f_{y-1}\right] \end{bmatrix} \times \begin{bmatrix} e^{-s_1 f_{y-1}} \\ -r_{y-1-a_0} e^{-s_1 f_{y-1}} \\ -r_{y-1-a_0} e^{-s_1 f_{y-1}} \end{bmatrix}$$

so that

$$\begin{aligned}\mathrm{Var}\left[N_{2,y}\right] = e^{-2 s_1 f_{y-1}} \big(&\mathrm{Var}[r_{y-1-a_0}] + \mathrm{Cov}(r_{y-1-a_0}, s_1) + \mathrm{Cov}(r_{y-1-a_0}, f_{y-1}) + \\ &r^2_{y-1-a_0} \left(\mathrm{Cov}(r_{y-1-a_0}, s_1) + \mathrm{Cov}(r_{y-1-a_0}, f_{y-1}) + \mathrm{Var}[s_1] + 2\mathrm{Cov}(s_1, f_{y-1}) + \mathrm{Var}[f_{y-1}]\right)\big)\end{aligned} \tag{8.18}$$

In most cases, confidence limits about a summary estimate $\hat{\Phi}_i$ can be approximated with

$$\hat{\mathrm{CL}}_{\Phi_i} = \hat{\Phi}_i \pm 2\sqrt{\hat{\mathrm{Var}}\left[\hat{\Phi}_i\right]}. \tag{8.19}$$

The exceptions in SURBA are those estimates which are generated as monotonic transformations of parameter estimates. For example, recruitment in year y is given by

$$\hat{R}_y = \ln \hat{r}_y.$$

In these cases SURBA uses $\hat{\mathrm{Var}}[\hat{r}_y]$ to generate confidence intervals on the log scale, which are then back-transformed to the required arithmetic scale. Thus the confidence interval for recruitment $\hat{R}_y$ would be given by

$$\hat{\mathrm{CL}}_{R_y} = \exp\left(\ln \hat{R}_y \pm 2\sqrt{\hat{\mathrm{Var}}\left[\ln \hat{R}_y\right]}\right).$$

It is important to note that the delta approach has proven to be very difficult to implement for composite measures such as SSB. Equation 8.18 is a fairly awkward calculation, and that is only for a single abundance estimate. To estimate the variance on SSB in a particular year using the delta method would require a very complicated calculation indeed – not impossible, but difficult to code correctly. For this reason, version 3.0 of SURBA only provides inferred variance estimates for mean Z and recruitment.

8.3.3 Modifications for SURBAR

SURBAR is a relatively new implementation of SURBA, written using the R package (R Development Core Team 2011) and dating from ICES (2009a). Parameters are estimated by nonlinear least-squares regression using the `nls.lm` function in the R `minpack` library (Elzhov et al. 2010). To generate uncertainty estimates, the Hessian $\mathbf{H}$ of this model fit is used to define a multivariate Normal distribution of the model parameters, and the R function `mvrnorm` (Venables and Ripley 2002, Ripley 2011) is applied to draw 1000 samples from this distribution. This generates 1000 values of the required s_a, f_y and r_{yc} parameters in such a way that their variance-covariance structure from the Hessian is maintained. Each of these parameter resamples is then used in turn to produce estimated time series of mortality and relative abundance, and I derive a 95% confidence interval about these fitted time series from the 2.5% and 97.5% quantiles of these 1000 curves at each age. This is a far simpler and more powerful procedure than the delta method used in SURBA 3.0. Needle and Hillary (2007) have shown that the methods give equivalent results for simple models. In SURBAR, I have also avoided the use of loops and data-frames in the estimation function, so run-times are comparable with the Fortran-90 version (and hence NAG library routines can be dispensed with).

8.3.4 Application to North Sea haddock

Figures 8.1 to 8.3 show the results of a SURBAR run for North Sea haddock, using data provided to the relevant 2011 ICES assessment working group (ICES 2011c). Five survey series were used for this run. Figure 8.1 gives the estimated time-series for mean mortality Z (ages 2 to 4), relative spawning stock biomass (SSB), relative total biomass (TSB), and relative recruitment (these results are "relative" in the sense that their scale is determined by the average values of the survey indices on which they are based, and cannot be interpreted as absolute estimates). 90% confidence intervals (shown as grey bands) are tight for this analysis. Figure 8.2 shows the corresponding survey log residuals for each of the five survey series used: here there is some evidence of trends in survey residuals (which could indicate changing survey catchabilities).

Finally, Figure 8.3 gives the results of retrospective analyses, generated by successively removing the last data-point from each series and re-estimating parameters. In this case, ten such retrospective runs have been performed, and the estimates of mortality, biomass and recruitment are very consistent: in other words, there is little retrospective bias. For North Sea haddock, the SURBAR assessment is used in an exploratory sense only: advice is still based on a catch-at-age approach (ICES 2011c)

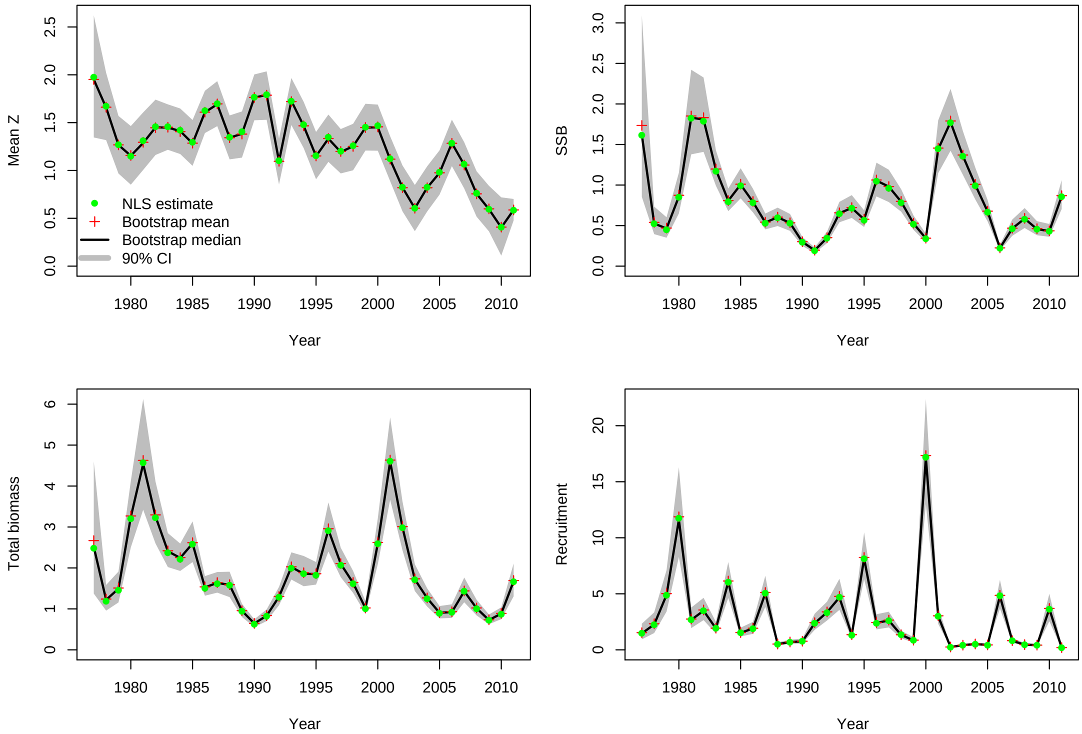


Figure 8.1: North Sea haddock 2011: SURBAR summary plots. Mean mortality Z (ages 2 to 4), relative spawning stock biomass (SSB), relative total biomass (TSB), and relative recruitment. Shaded grey areas correspond to the 90% CI. Green points give the model estimates, while red crosses and black lines give (respectively) the mean and median values from the uncertainty estimation bootstrap. Data source: ICES (2011c).

The relevance of this brief summary to the aims of this thesis is that survey-based assessment methods have been developed, and have the potential to provide useful advice to fisheries managers when catch data are unavailable or misleading. Survey data often have spatial structure (in terms of sampling strata or unfishable areas), and evaluations of the potential of survey-based management and advice need to be able to account for such structure. This Section on survey-based assessment methods therefore highlights another potential benefit of the spatial model outlines in Chapter IV.

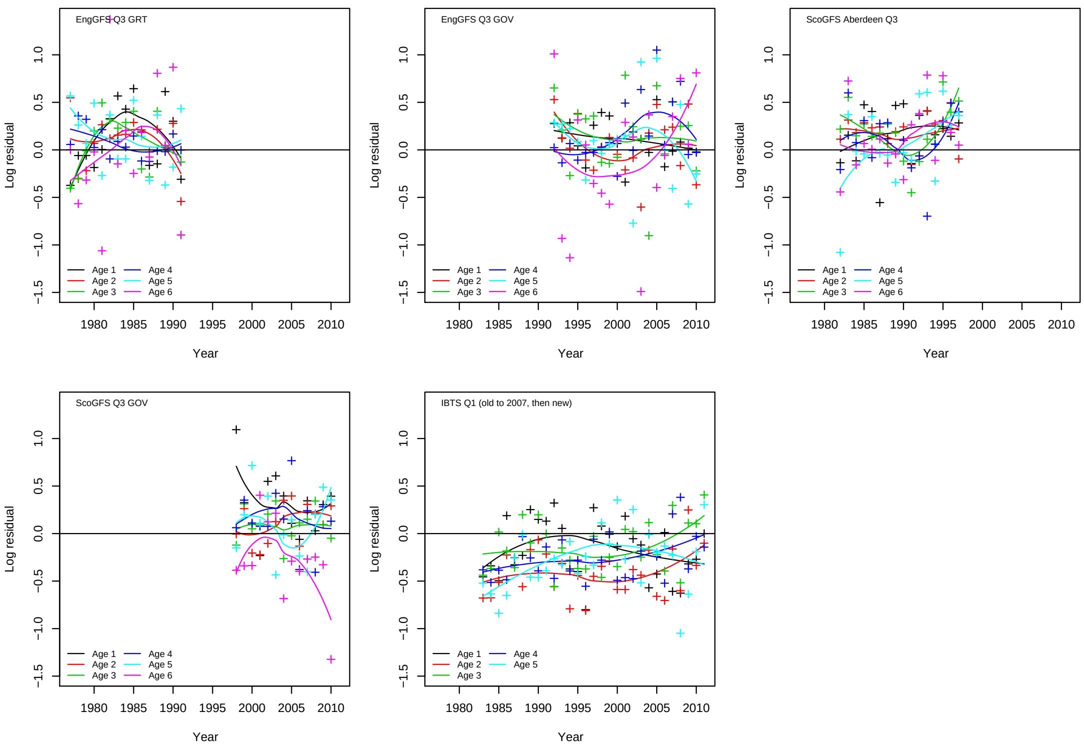


Figure 8.2: North Sea haddock 2011: survey residuals. Lines are loess smoothers fitted through each residual time-series. Data source: ICES (2011c).

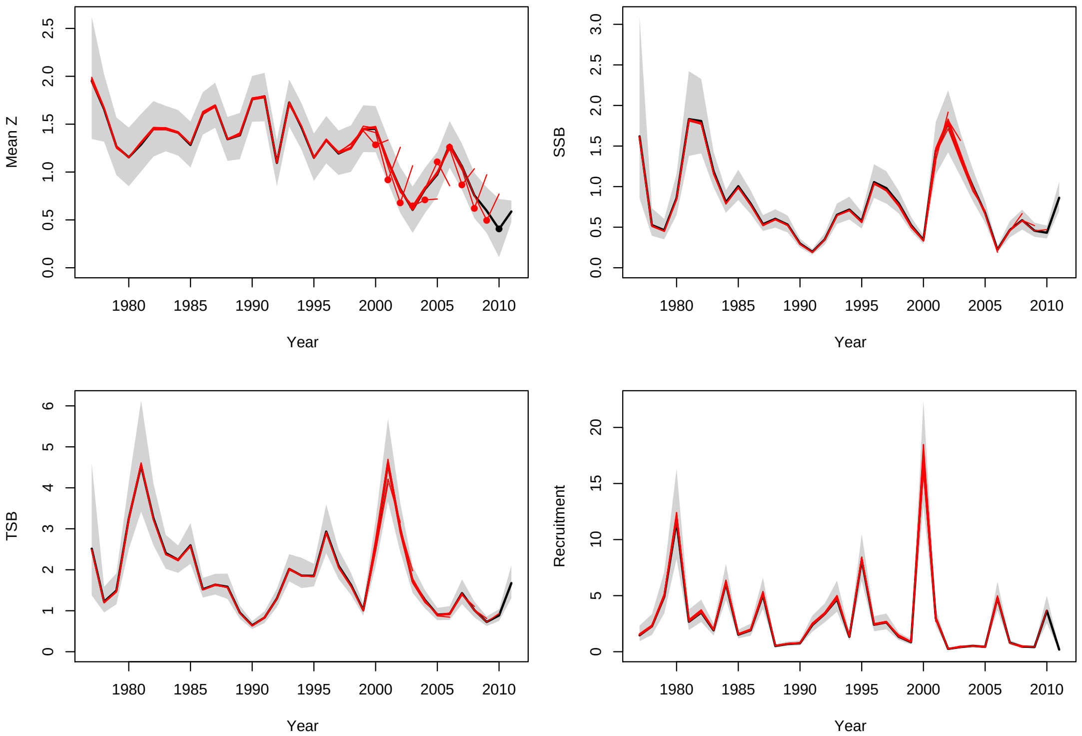


Figure 8.3: North Sea haddock 2011: SURBAR retrospective plots. Mean mortality Z (ages 2 to 4), relative spawning stock biomass (SSB), relative total biomas (TSB), and relative recruitment. Shaded grey areas give the 90% CI of the full time-series run. Black lines give the full time series run, red lines show each retrospective run. For mean Z, the black and red dots gives the final true estimate for each time-series: the following value in each case is a simple three-year mean and has not been estimated directly. Data source: ICES (2011c).

9 Conclusions

This Chapter has presented four management strategy evaluations for haddock stocks in European waters, addressing the following principal issues in each case:-

North Sea haddock Development of evaluation code to deal with the sliding-F rule through iteration; presentation of the problems arising from a simplistic model of discarding practice.

North Sea haddock with banking-and-borrowing Demonstration of the flexibility in the North Sea haddock evaluation code.

West of Scotland haddock Extension to accommodate a more complex assessment structure including landings, discards and unaccounted removals.

Rockall haddock Implementation of revised FLR libraries, greatly increasing analysis speed and allowing for much more complete exploration of confidence intervals.

These analyses have served to progress the science of management strategy evaluations in European haddock fisheries, and have formed the basis of successful intergovernmental agreements on fisheries management that have contributed to the maintenance of sustainable haddock stocks (ICES 2011c, ICES 2011d). However, they have not been able to address the issue of modelling appropriately changes in how fishermen operate in the face of imposed regulation changes, particularly with regards to how a fishermen decides whether to throw a fish away or not. As fish stocks and fish markets are unevenly distributed in space, fishing is clearly an activity with a strong spatial component that these evaluations do not consider.

Further discussion Sections in this Chapter have considered alternative management approaches such as quota points, and survey-based assessment and management. These, along with such common measures as closed areas, also all have (or should have) explicitly spatial aspects to them, either through spatial fleet responses or through spatial characteristics of surveys and other fisheries data.

In conclusion, in this Chapter I have shown that any model of fleet dynamics and fisheries data must be able to simulate spatial responses to change as well as temporal. The remainder of this thesis attempts to contribute to the development of such a model.

Chapter III

Characterising fleet dynamics

10 Background

Scientific advice for fishery management has always been based on limited data (Kruse et al. 2005). Catch data often do not include discards (ICES 2011c), and survey indices are derived from brief snapshots of stock abundance and distribution (ICES 2011b). Such limitations hamper the ability of scientists to help managers to take appropriate decisions. Historically, one of the key missing pieces of information has been the location and intensity of fishing effort (see, for example, ICES 2001). Without good data on where and how much vessels have been fishing, it has been very difficult to devise and implement appropriate management measures that take account of the spatial distributions of fish or fleets.

Vessel Monitoring System (VMS) data consist of vessel speeds, headings, and locations, with one reading (known as a "ping") being transmitted to a central repository via a satellite link on a regular time schedule. In the current Scottish system pings are transmitted every 2 hours, although this is a regulatory rather than a technical restriction. Although not without problems, the recent availability of VMS data to scientists has permitted a wide range of analyses that would not previously have been possible. Many studies have focussed on improved estimates of fishing effort distribution (Borchers et al. 2009, Lee et al. 2010, Vermard et al. 2010, Gerritsen and Lordan 2011), while a smaller number have used VMS data further to analyse aspects of fishing decision-making (see, for example, Rijnsdorp et al. 2011). In this chapter, I follow Needle and Catarino (2011) and consider the response of Scottish demersal whitefish skippers to the implementation of real-time closures (RTCs), which are part of the Scottish Government's response to European Union (EU) calls for reductions in cod (*Gadus morhua*) mortality. Using VMS data and a derived spatio-temporal distribution indicating the relative importance of cod, I analyse the movements of those vessels thought to be most directly affected by RTCs. Specifically, I determine whether vessels moving away from closed areas (or back towards reopened areas) increase or decrease their likely impact on cod mortality, as measured by the RFII (relative fish importance index) for cod in the areas in which they are fishing.

Needle and Catarino (2011) focussed on the years 2008 and 2009, and considered cod only. In the first part of this chapter, I extend this work to include data from 2010. I consider firstly a relative index of fish abundance, which is required in order to determine whether vessels are moving towards or away from areas of high fish density. I then develop a method for presenting VMS data which does not infringe commercial confidentiality. Next I look into data from Remote Electronic Monitoring (REM) management schemes, and present a method for using such data to test the widely-used assumption that the "speed" component of VMS data can be used to determine activity as well as location. I then provide information on Scottish real-time closures during 2008-2010, and develop a methodology for estimating the difference between the relative fish abundance values from two locations (and the distance between those locations). I present the results of all these analyses for a specific vessel in 2009, and for all vessels during 2008 to 2010.

The final Section of the Chapter considers how VMS data can be used to characterise changes in fishing locations used by particular vessels in particular quarters from year to year. I use cluster analysis to determine discrete fishing areas, then evaluate whether any significant location changes can be related to changes in the density of real-time closures in those discrete areas. This analysis approaches the question of response to closures in a different way, allowing for consideration of the possible effects of closures on the entire fleet (that is, not just those fishing directly in closed areas soon before or soon after the time-period covered by the closures).

These analyses are useful in themselves for evaluating the impact of management measures on fish mortality, and as examples of how to use fishery-dependent information to provide management advice that would not otherwise be obtainable. More importantly for the aim of this thesis, they are case studies of how to begin to characterise the likely response of fishing fleets to management measures. Without such a characterisation, it would be impossible to develop the kind of spatio-temporal simulation models that I will consider in the final section of the thesis. For example, if a vessel travels a long way from a cod closure to reach another good cod area, then the skipper may be thinking of himself as principally a cod fishermen rather than a profit maximiser (the latter would factor fuel costs more strongly into their planning). If he switches to fishing on *Nephrops* (that is, prawns) in a nearby location using different gear, then he may well be a profit maximiser. A functional fisheries simulation would need (ultimately) to be able to account for these factors.

Note that parts of this chapter are based on the methodology and data analysis presented in Needle and Catarino (2011, reproduced in Chapter VI). My co-author in this paper (Rui Catarino, Marine Laboratory, Aberdeen) has confirmed that the methods, results and analyses presented here are solely my own work (see page 5).

11 Developing a relative index of fish importance

11.1 DATA

In order to generate a spatio-temporal distribution of relative fish importance, and thereby estimate whether vessels move towards or away from aggregations of different species as the result of area closures or other management measures, reliable data on observed fish density is required. Reported landings records have limited utility for this purpose, as a) they do not include discards, which may be a sizeable component of the catch, and b) they can be very non-specific about where fish were caught. The reported landings for a fishing trip can in theory be assigned equally to all the VMS fishing-ping locations for that trip, but this is imprecise and could be misleading. Appropriate models of fish distribution that can incorporate landings records are in development, but in the meantime I concluded that they could not be used for this analysis.

The data used, therefore, come from a combination of research-vessel surveys and discard observations. The data for 2008–2010 were as follows:

1. The North Sea International Bottom Trawl Survey (IBTS NS Q1 and Q3), carried out by several countries during January-February and July-September, and collated by ICES.

2. The Beam Trawl Survey (BTS Q3), conducted in the southern North Sea during August and September, and also collated by ICES.

3. The Scottish Groundfish Survey in Division VIa (West of Scotland), carried out by Marine Scotland on RV *Scotia* during March (ScoGFS VIa Q1).

4. The Scottish Rockall Survey (Rockall Q3), conducted by Marine Scotland on RV *Scotia* at Rockall during September.

5. Scottish discard observations, collated from around 75 Scottish observer trips each year.

Data were taken from the ICES DATRAS database (see `www.ices.dk`), as well as the Scottish Fisheries Management Database (FMD) maintained by Marine Scotland (see `www.scotland.gov.uk`). As an example, the locations of available observations for February 2010 are plotted in Figure 11.1, while all the available data for 2008-2010 are summarised in Figure 11.2.

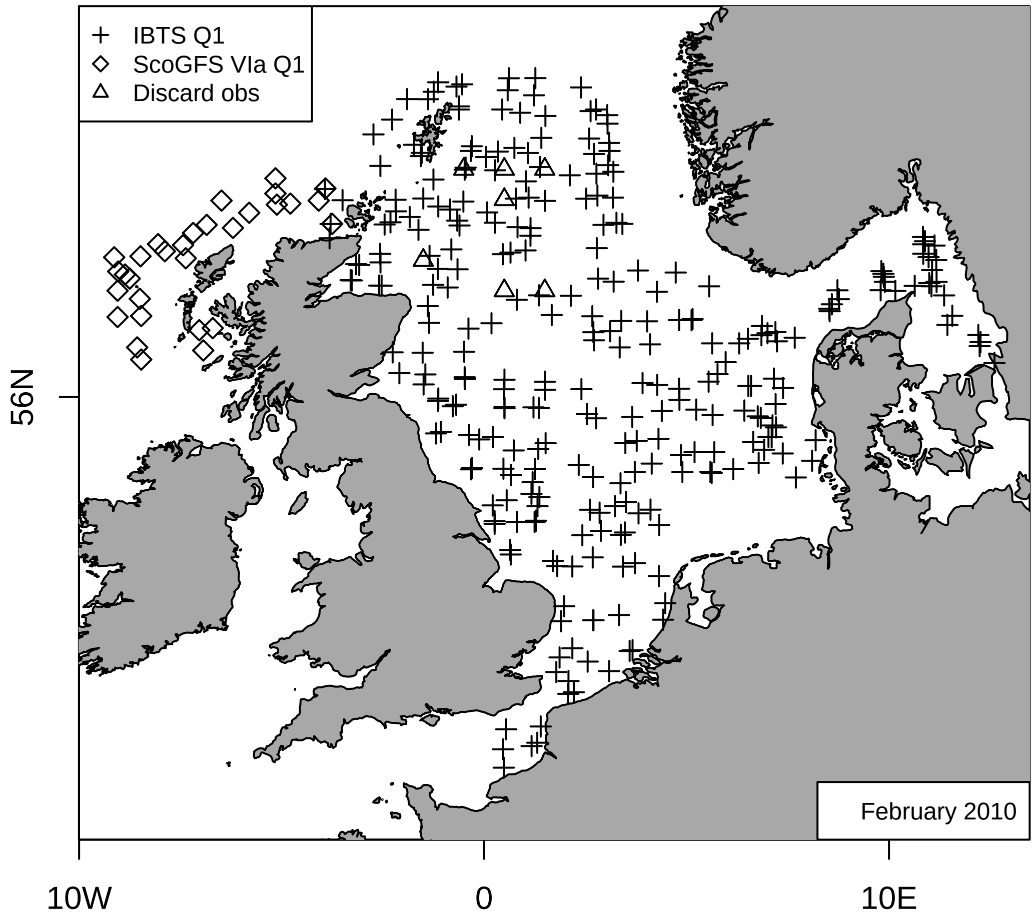


Figure 11.1: Locations of the observations of fish density used in the generation of the relative fish importance index (RFII). Symbols indicate locations of available observations for February 2010.

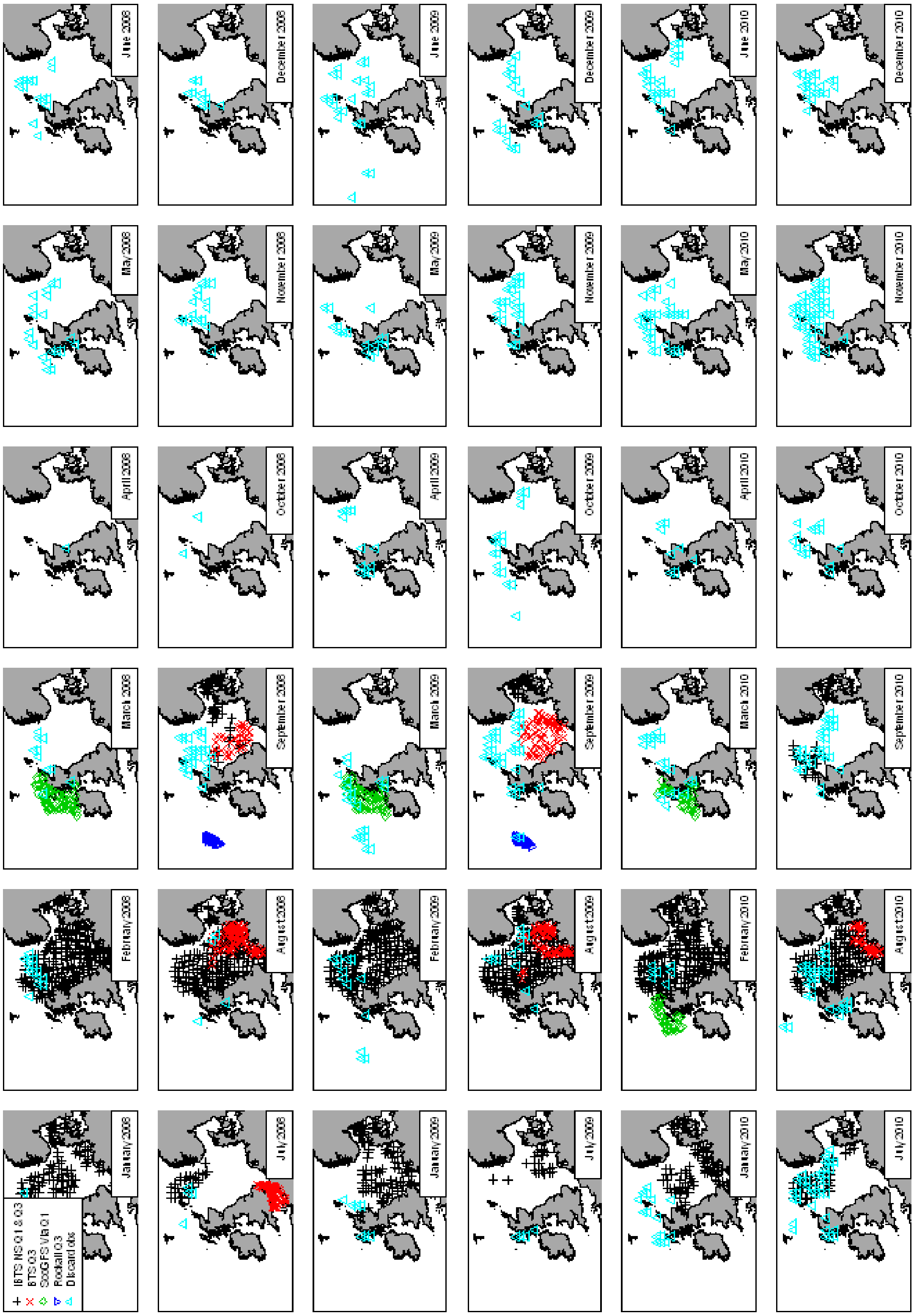


Figure 11.2: Locations of the observations of fish density used in the generation of the relative fish importance index (RFII). Symbols indicate locations of available observations for all months during 2008-2010.

11.2 GENERATING THE RELATIVE FISH IMPORTANCE INDEX (RFII)

In order to determine whether vessels move to areas of greater or lesser apparent cod density when displaced by the imposition of an RTC, Needle and Catarino (2011) developed an index of relative cod density called the Relative Cod Importance Index (RCII), which here is generalised and referred to as a Relative Fish Importance Index (RFII). In brief: this takes all the available spatial fish observation data from research-vessel surveys and discard observer trips for a given month, standardised to lie on a consistent scale (since measurement units used by different surveys and observer programmes can vary widely), then fits a trend surface using generalised least-squares regression smoothing. This procedure produces a contour plot of relative cod importance for each month. However, observations in a given month can be patchy, and for some months there are no observations at all. To improve the consistency of fitted distributions through time, an additional temporal smoothing step is used, in which the distribution at each point for a given month is modified by the equivalent values in preceding and succeeding months. Temporal smoothing is achieved using weighted local polynomial regression (loess) smoothers (Cleveland et al. 1992), in which the weights are the means of the Haversine distances (see Equation 11.2) from the point in question to the nearest points with actual observations in that month. Therefore, a relative fish distribution is generated using observed fish abundances, smoothed over both space and time to avoid problems inherent in the patchiness of the data. All analyses in the section were carried out using R (R Development Core Team 2011, version 2.8.1), with the `spatial` library (Venables and Ripley 2002).

The RFII algorithm proceeds as follows. Numbers of fish N caught per hour (either by a survey or by an observed vessel) are extracted from the relevant datasets. Fish numbers from each data source are generally heavily skewed, with many zero observations and a few large observations. If used without any transformation, these data could lead to fish distribution maps consisting of two or three "hot spots," and this pattern does not often reflect well the industry perception of more widespread fish abundance on which fishing decisions are based. As I am attempting to model the results of such decisions here, a distribution based on untransformed data (although tractable if modelled with an appropriate extreme value distribution) would be difficult to interpret. To improve the distributional properties of the data for the purposes of this analysis, therefore, a cube-root transformation $N^{\frac{1}{3}}$ is applied. The effect on data distributions is illustrated in Figure 11.3.

It should be noted that the choice of transformation is *ad hoc* and possibly not ideal: zero-inflated models (Zuur et al. 2009) would be examples of plausible alterna-

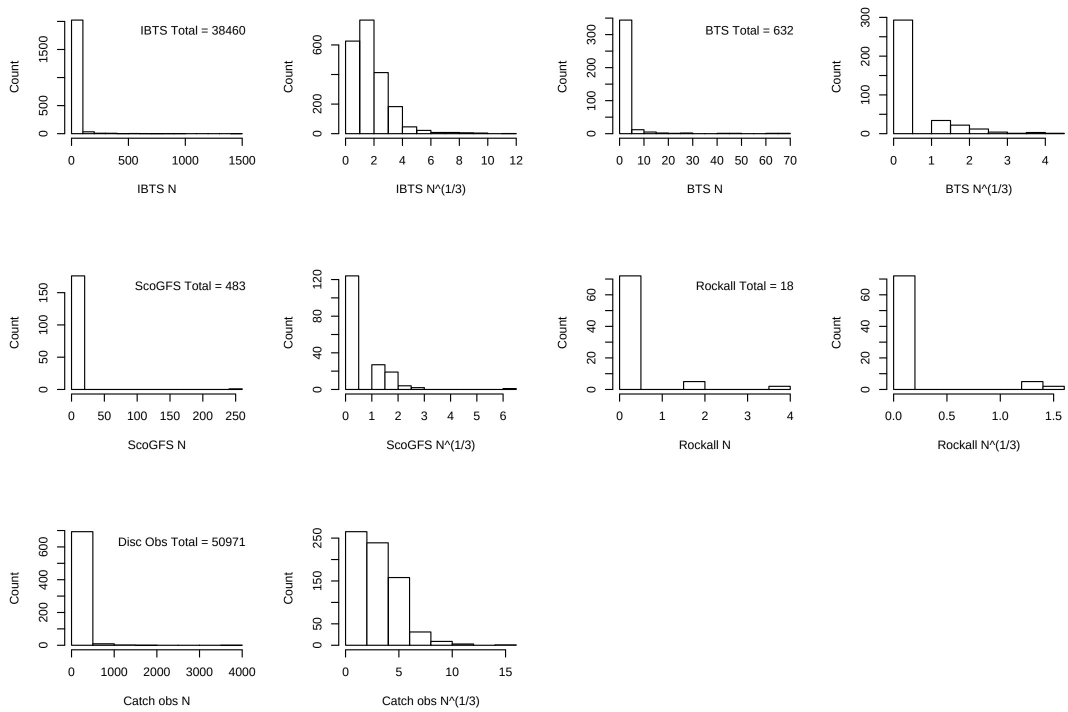


Figure 11.3: Histograms of cod abundance during 2008-2010 in data sources used for estimation of the RFII for cod. For each data source, the left plot gives untransformed abundance N, while the right plot gives the cube-root transform $N^{\frac{1}{3}}$.

tives. The cube-root transform reduces to a certain extent the extreme skewness of the raw data distributions, although it does not normalise them and the problem of many zero observations is not addressed. It may also not be fully appropriate to attempt to generate smooth distributions for species in which patchiness could play an important rôle in stock dynamics. Needle and Catarino (2011) argued that the cube-root transform was a reasonable approach in the first instance, as it reduced the propensity for the method to produce very localised points with high importance indices (which in any case are largely a function of low sample sizes), and thereby enabled appropriate inference on the likely effect of vessel movements. Alternative transformations should be explored in future work, along with alternative abundance measures such as biomass.

Next, fish abundance data are further rescaled so that relative abundance over all observations lies between 0 and 1, thus permitting direct comparison between data from different sources which may use very different measurement units. This rescaled abundance is denoted by $\tilde{N}^{\frac{1}{3}}$. Abundance data from all sources are collated into a single dataset, and then split by months. Land areas are bounded by set of zero-valued observations located along all coastlines. The `surf.gls` function in R (Ripley 2011) was used to fit trend surfaces: I implemented this with a polynomial surface of degree

2 and an exponential covariance structure (Venables and Ripley 2002). `surf.gls` will fail if two or more observations have exactly the same positions. To prevent these computational problems when fitting trend surfaces, small random perturbations are applied to the lat-long position records of all observations.

The dataset for a given month now contains a list of rescaled abundances along with a unique lat-long position marker for each. `surf.gls` is now applied to these data for each month, to generate trend surfaces on the basis of values of $\tilde{N}^{\frac{1}{3}}$. This approach assumes an heteroscedastic error structure in the underlying abundance distribution, which the cube-root transform has not really provided (and which therefore is a potential source of bias). As part of the fitting process presented for cod in Needle and Catarino (2011), a mask is applied to ensure that land areas (depth > 0 m) and deep-water areas (depth < -250 m) are excluded from the fitted distribution, as cod are unlikely to be found in either. This mask can be made specific to the particular stock under consideration. The results of this first stage of RFII generation for cod during the first four months of 2010 are given in the distributions presented in Figures 11.4 to 11.5, and for all months of 2008-2010 in Figure 11.6.

The distributions presented in Figures 11.4 to 11.6 are independent from each other, in that the distributions for a given month have no links (explicit or otherwise) with either the preceding or the following month. In order to implement time-dependency, and in so doing to provide information for those months with few or no observations, the next step is to apply temporal smoothing through a weighted loess regression time-series smoother. Weights are calculated using the mean inverse Haversine distances of the point of interest (x_i, y_i) to the n available abundance observations for that month.

For an angle θ, the Haversine function is given by

$$\text{haversin}(\theta) = \sin^2(\theta/2) \tag{11.1}$$

and the Haversine formula (Gellert et al. 1989) is then

$$\text{haversin}(d/R) = \text{haversin}(\phi_2 - \phi_1) + \cos(\phi_1)\cos(\phi_2)\,\text{haversin}(|\lambda_2 - \lambda_1|) \tag{11.2}$$

where d is the spherical distance between points, R is the radius of the sphere (in this case, the Earth), and (ϕ_1, λ_1) and (ϕ_2, λ_2) are the latitude and longitude of the first and second points respectively. The required distance d can be calculated from Equation 11.2 using the inverse Haversine function, so that

$$d = R\,\text{haversin}^{-1}\left(\text{haversin}(\phi_2 - \phi_1) + \cos(\phi_1)\cos(\phi_2)\,\text{haversin}(|\lambda_2 - \lambda_1|)\right). \tag{11.3}$$

The loess smoother weight $\omega_{i,m}$ for the ith point (x_i, y_i) in month m is then given by the inverse of the means of the Haversine distances between the ith point and all other extant points in that month. This approach is used rather than Euclidean distances, as it accounts for the curvature of the Earth: however, the Haversine formula does assume a perfectly spherical Earth (rather than the actual ellipsoid), and may be up to $\pm 0.5\%$ inaccurate.

The intention with this weighting scheme is to produce an estimate for a given point in a given month that is strongly dependent on nearby observations, and only weakly determined by distant observations. These weights are then used in a weighted loess time-series smoother, which in addition to the monthly values includes the mean of the time-series as extra values in months 0 and 37: that is, at the ends of the time-series. These extra values are given a weight of 0.5 each in the smoother, and are intended to prevent potential extrapolation to negative values.

In Needle and Catarino (2011), the span of the loess smoother was set to 2.0, following exploratory analyses which indicated that this gave a reasonable balance between responsiveness and smoothness (although no formal statistical testing of this conclusion was carried out). Here this approach has been modified. For each point (x_i, y_i), loess smoothers with a range of spans in the set $\{0.25, 0.5, 0.75, 1, 2, 3, 4, 5\}$ were fitted to the time-series of RFII observations. For each fit, the small-sample Akaike's Information Criterion (AIC$_c$; Burnham and Anderson 2010) was determined using

$$\mathrm{AIC}_c = 2k - 2\ln L + \frac{2k(k+1)}{n-k-1} \tag{11.4}$$

where L is the likelihood of the smoother fit, n is the number of data points and k is the effective number of parameters (this is determined by the loess smoother itself). AIC$_c$ is interpreted in the same way as AIC, but accounts for relatively small sample sizes such as those used here.

The approach is illustrated for a point east of Shetland in Figure 11.7. This shows the loess fits for the the observation time-series for the eight different span values, along with the AIC$_c$ in each case. The plot to the bottom right of Figure 11.7 compares the AIC$_c$ for each span with the minimum observed AIC$_c$ for that point. Burnham and Anderson (2010) suggest that models for which the AIC$_c$ is within ± 1 of the minimum AIC$_c$ should be considered to be strongly supported. In Figure 11.7, this is the case for all spans except 0.25. The same result pertained for every point in the study area (unpublished results), suggesting that any span between 0.5 and 5.0 would be suitable for this analysis. I have used a span of 0.5 throughout the following analysis, as this generates fitted distributions that differ noticeably between months, and this seems more realistic than very smooth and unchanging distributions that would be produced by higher spans.

Examples of the smoother weights and the resultant smoothed RFII time-series for cod (assuming a loess span value of 0.5) at a point east of Shetland are given in Figure 11.8.

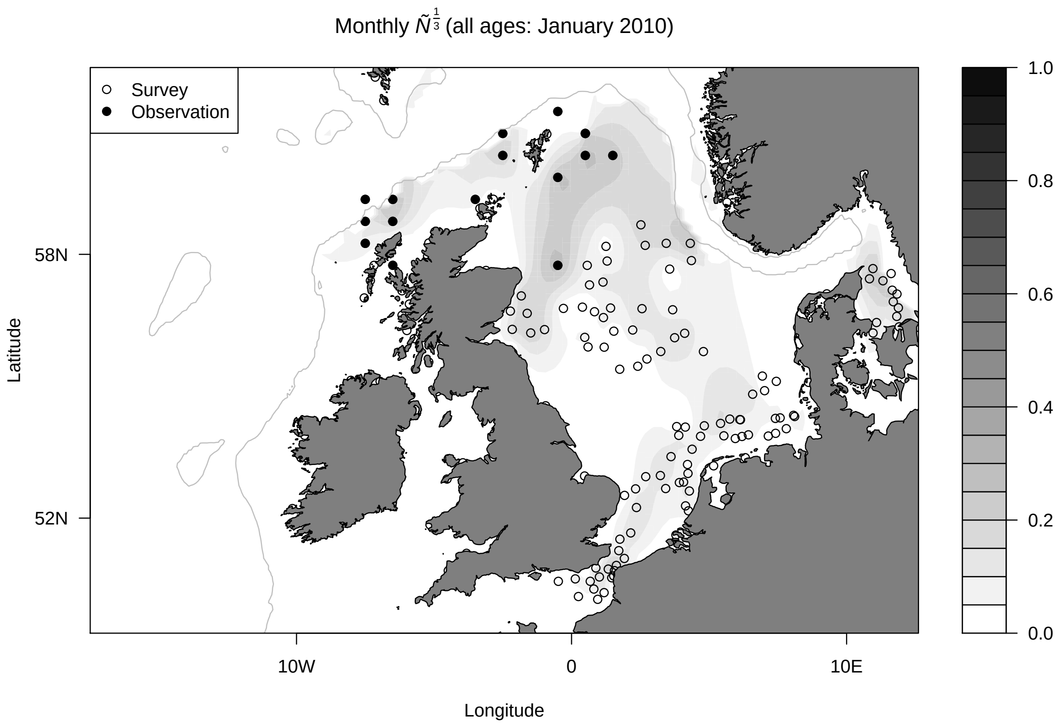
The final step is to collate (without further smoothing) all the smoothed index values for each month to generate a new smoothed density map for that month. The resultant monthly distributions are given in Figures 11.9 to 11.10 (for the first four months of 2010), and Figure 11.11 (for all months of 2008-2010).

The RFII as presented above (and, using an earlier iteration, in Needle and Catarino 2011) remains problematic, however. It is still at a relatively early stage of development, and may not yet be sufficiently detailed to permit robust evaluations of fleet behaviour at the appropriate scale. Specific potential problems with the RFII include:-

- No estimates of uncertainty are yet available.
- The use of two separate smoothing steps is neither parsimonious nor elegant.
- The abundance metric currently used is based on simple abundance counts. The age, length or weight structures in these data are ignored, with a potential loss of inference.
- There is no consideration made of the different selectivity characteristics of different fishing vessels. For example, a large year-class of young haddock might not be caught at all by commercial vessels (due to large cod-end mesh-size and other measures such as square-mesh panels), yet feature strongly in abundance indices from research-vessel surveys.
- The RFII estimates for cod for an area (such as Rockall) which always has relatively low but non-zero observations will be artificially inflated by the rescaling used here. Such areas will therefore appear to be more important than they actually are.

I am currently developing alternative, model-based methods to generate spatio-temporal distributions for cod and other species, taking account of uncertainty and additional information such as depth. Possible approaches include 3D smoothers such as `mgcv` in R (Wood 2011).

Any developments in this area will only ever be as good as the survey and observer data on which they are based. However, it should also be emphasised that the results reported in this paper do concur with what would have been expected given my experience of survey data and the fishing industry. I would contend that the results given in Section 13 are unlikely to be compromised by the extant deficiencies in the RFII methodology.



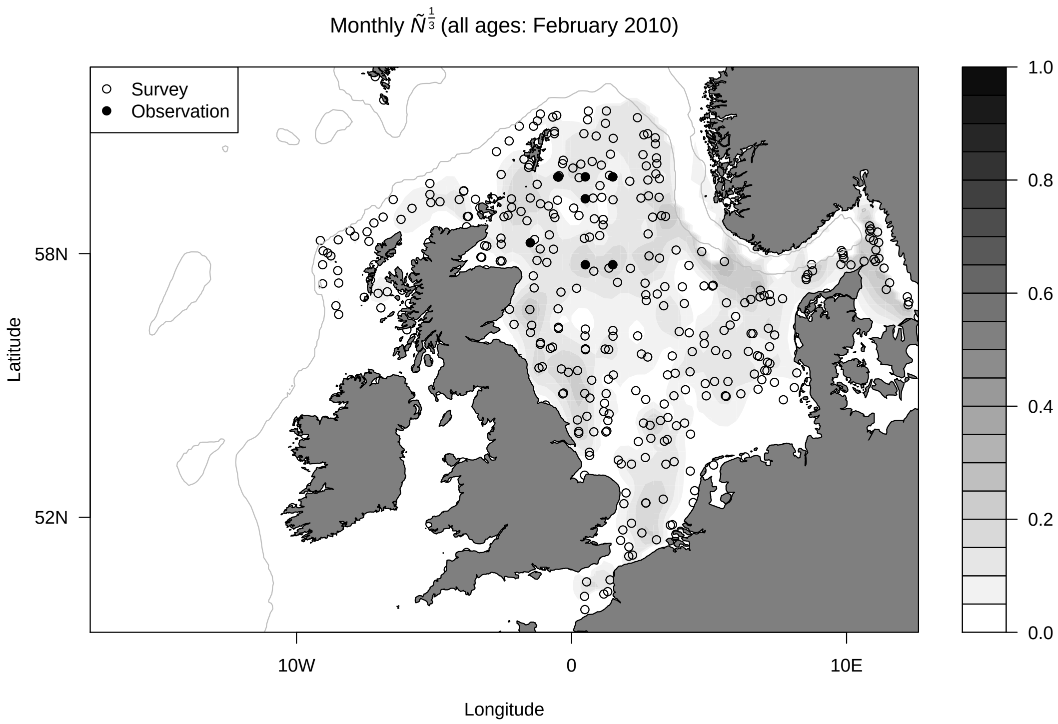
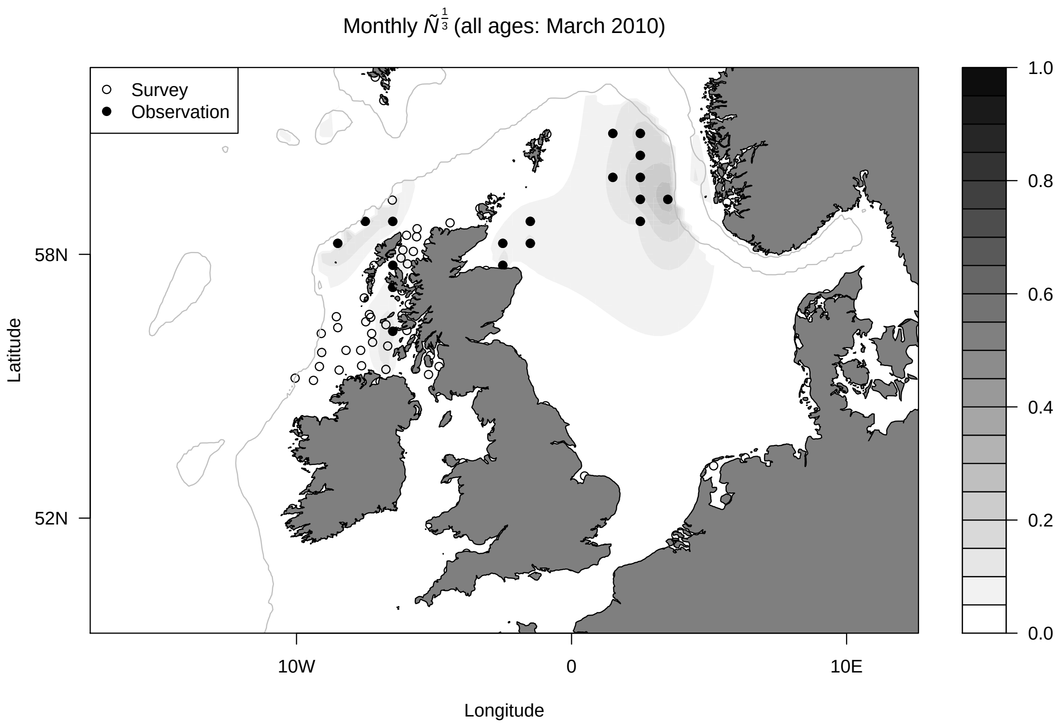


Figure 11.4: Fitted trend surface (without temporal smoothing) for rescaled cod abundance $\tilde{N}^{\frac{1}{3}}$ for January and February 2010. Grey lines indicate the 250-m depth contour, used as a mask for the fitted surface. Darker areas indicate higher $\tilde{N}^{\frac{1}{3}}$. Data points from research-vessel surveys are indicated by open circles, while data from observer trips on commercial vessels are shown by closed circles.



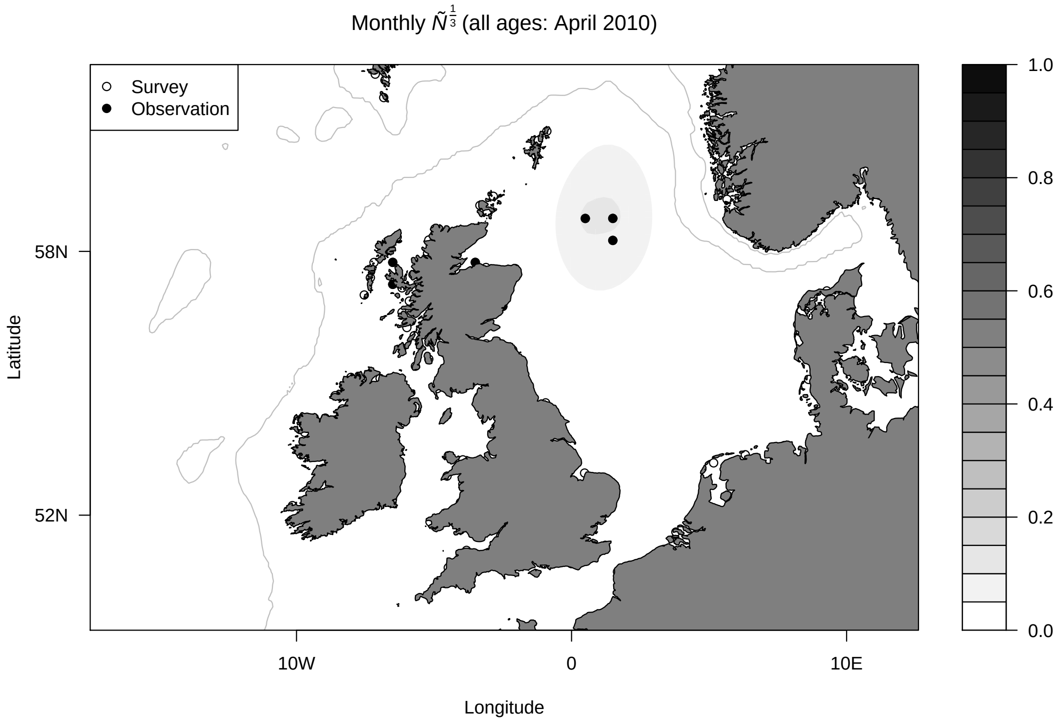


Figure 11.5: Fitted trend surface (without temporal smoothing) for rescaled cod abundance $\tilde{N}^{\frac{1}{3}}$ for March and April 2010. Grey lines indicate the 250-m depth contour, used as a mask for the fitted surface. Darker areas indicate higher $\tilde{N}^{\frac{1}{3}}$. Data points from research-vessel surveys are indicated by open circles, while data from observer trips on commercial vessels are shown by closed circles.

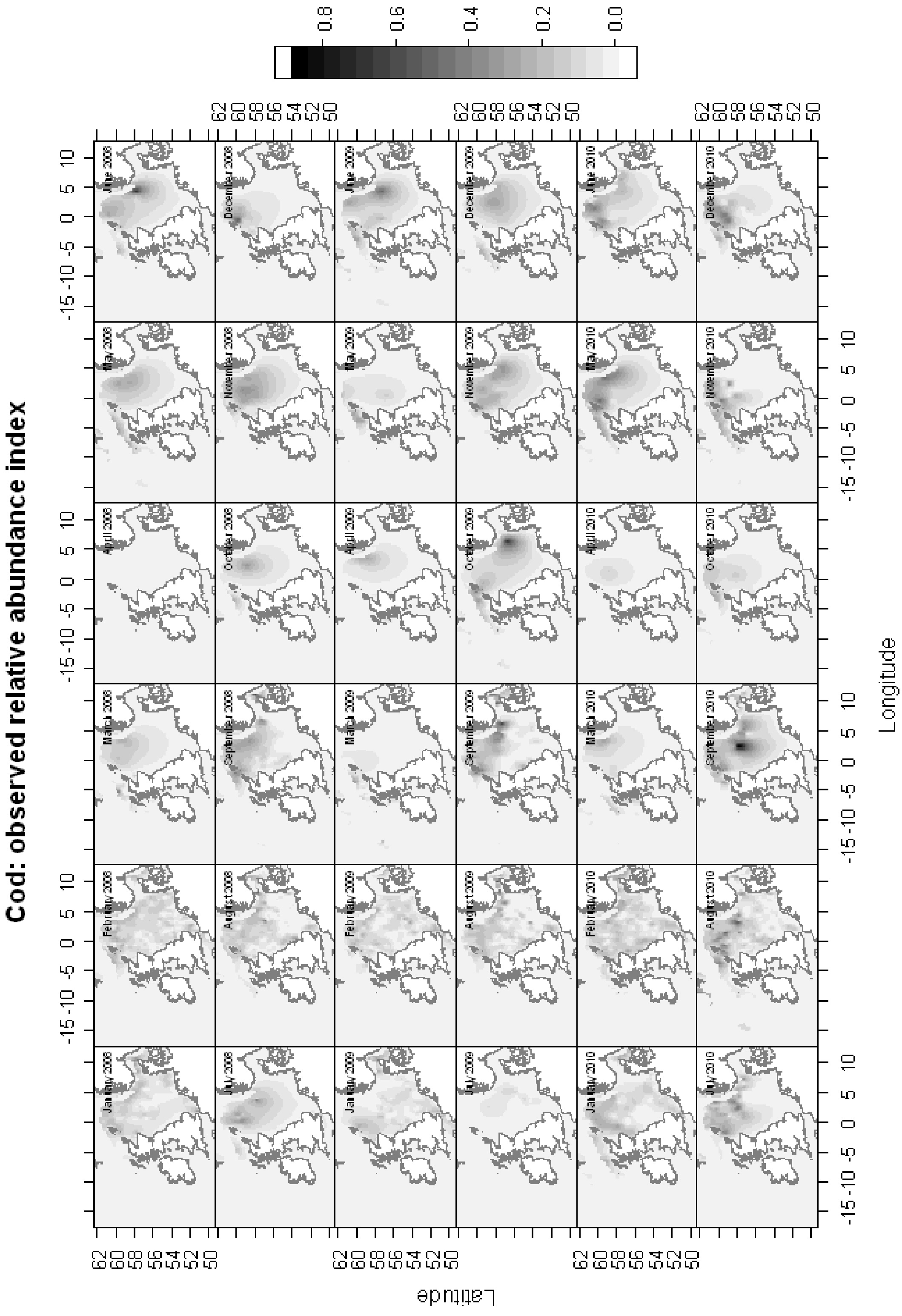


Figure 11.6: Fitted trend surface (without temporal smoothing) for rescaled cod abundance $\tilde{N}^{\frac{1}{3}}$ for all months during 2008-2010. Darker areas indicate higher $\tilde{N}^{\frac{1}{3}}$.

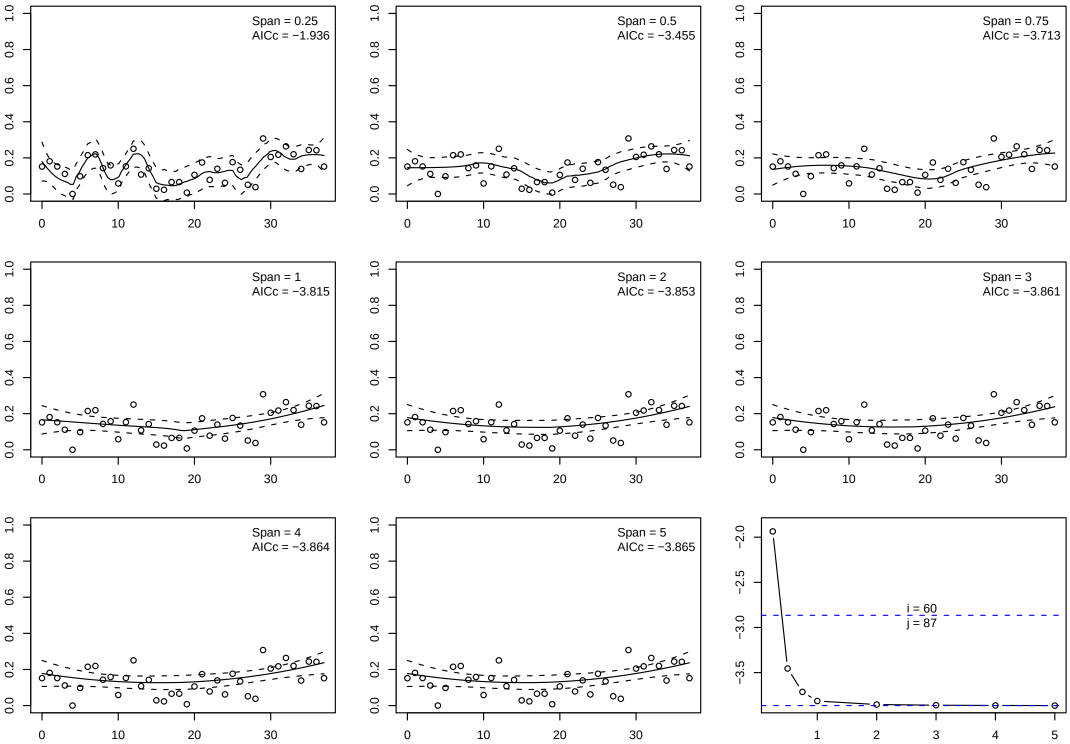


Figure 11.7: Monthly RFII values for cod for 2008-2010 at a point to the east of Shetland, along with weighted loess smoothers (solid line) with 95% confidence limits (dotted lines). Loess spans range from 0.25 (top left) to 5.0 (bottom middle). Loess weights are not shown here. AIC_c values for each loess fit are indicated. Points in months 0 and 37 indicate the means of the full time-series, which were included in the smoother estimation (with weights of 0.5) to prevent unrealistic extrapolation. The summary plot (bottom right) gives all the AIC_c results (the *x*-axis for this plot gives the loess spans). Dashed blue lines show $\min \mathrm{AIC}_c$ (lower) and $\min \mathrm{AIC}_c + 1$ (upper).

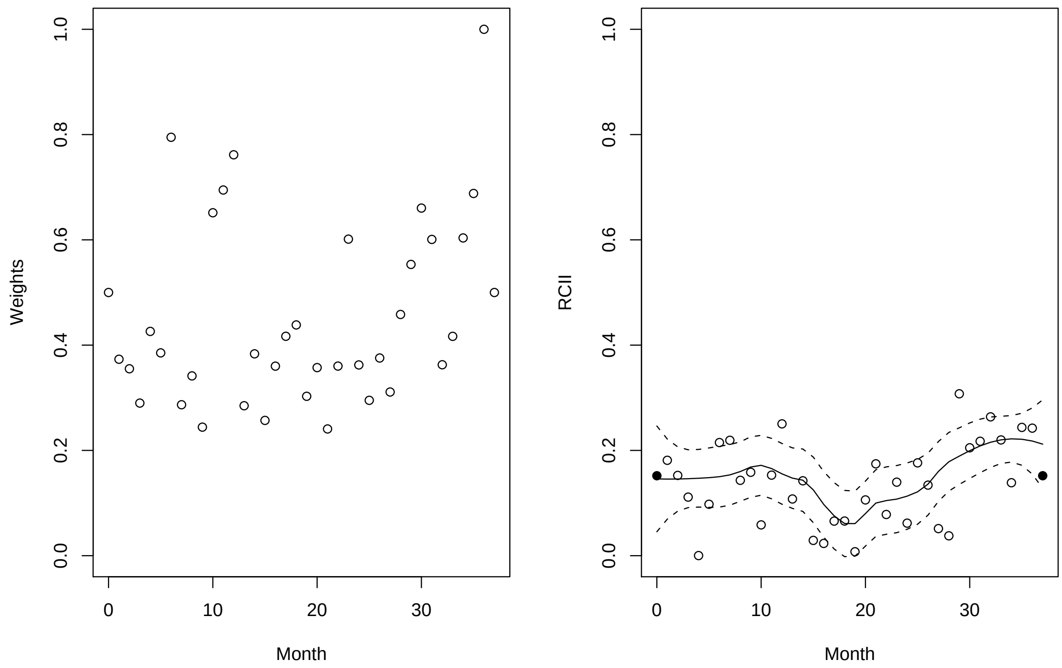
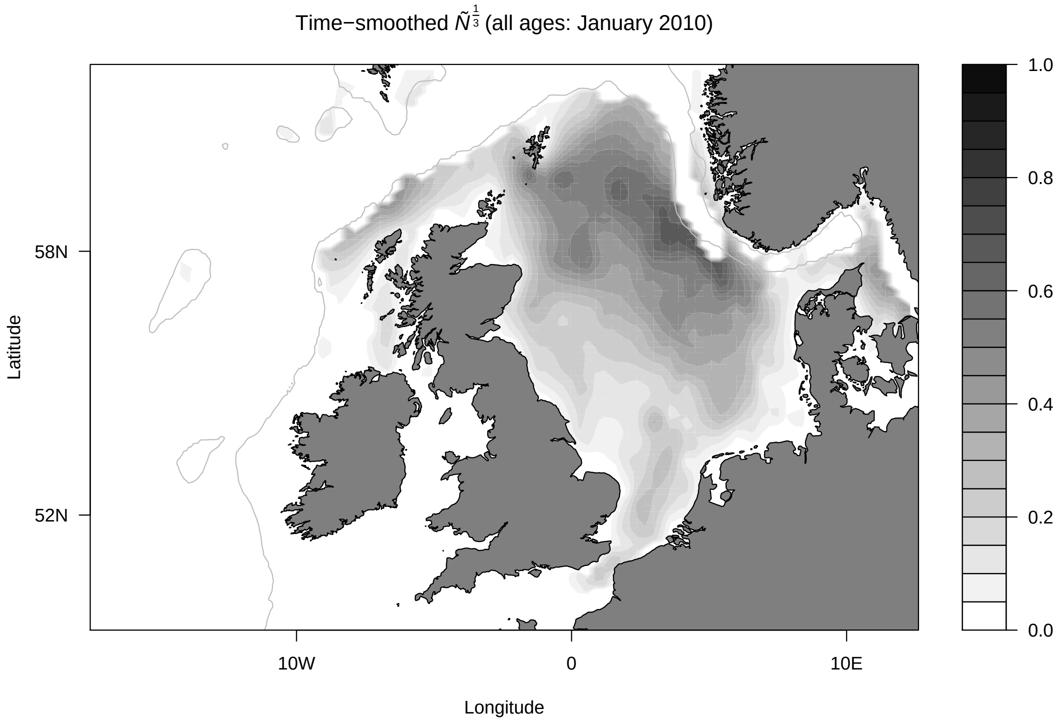


Figure 11.8: Left: mean Haversine-distance weights for the temporal loess index smoothing at a point off the east coast of Shetland, for 2008-2010. Right: monthly RFII values for cod for 2008-2010, along with a weighted loess smoother (solid line) with 95% confidence limits (dotted lines). The loess span was set to 0.5. Solid points in months 0 and 37 indicate the means of the full time-series, which were included in the smoother estimation (with weights of 0.5) to prevent unrealistic extrapolation.



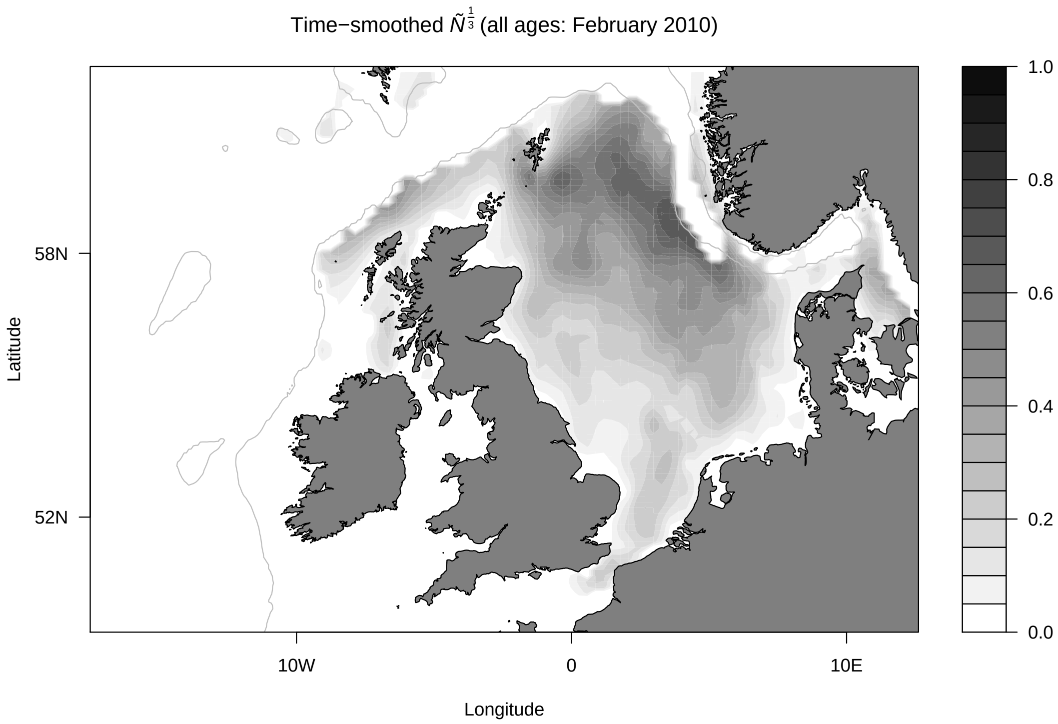
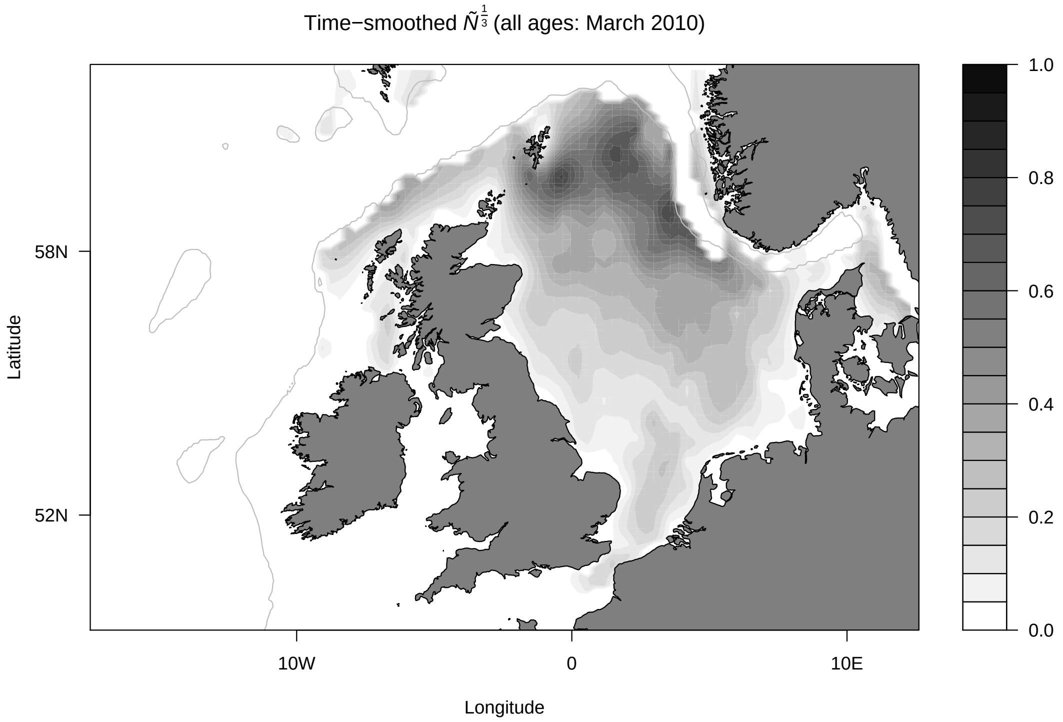


Figure 11.9: Fitted trend surface (with temporal smoothing) for rescaled cod abundance $\tilde{N}^{\frac{1}{3}}$ for January and February 2010. Grey lines indicate the 250-m depth contour, used as a mask for the fitted surface. Darker areas indicate higher $\tilde{N}^{\frac{1}{3}}$.



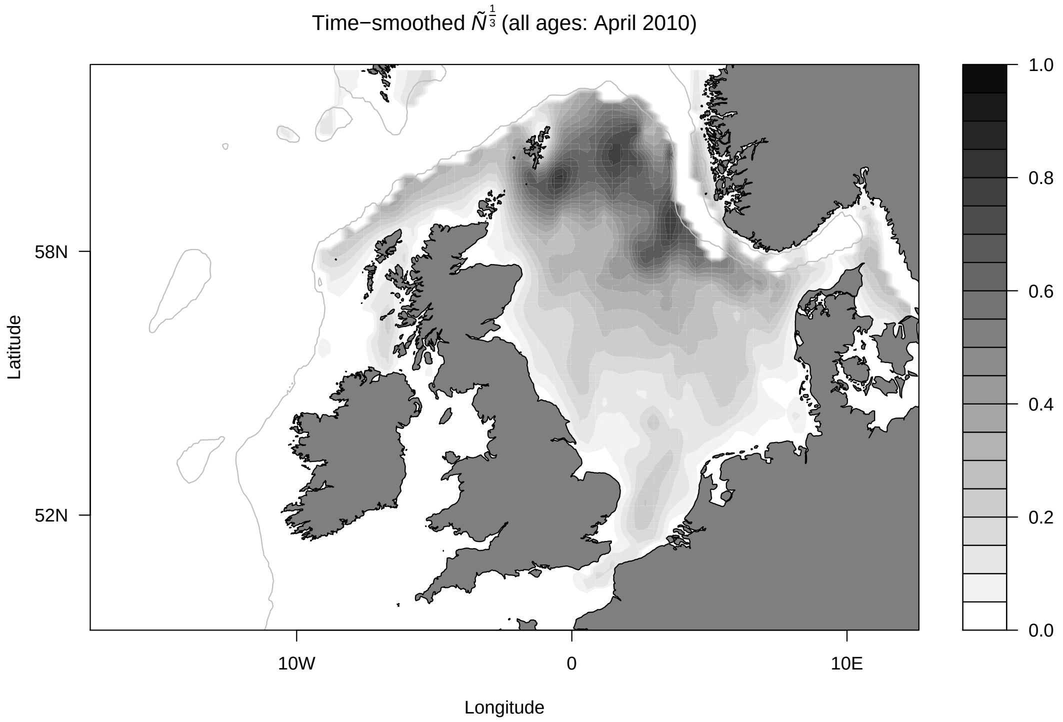


Figure 11.10: Fitted trend surface (with temporal smoothing) for rescaled cod abundance $\tilde{N}^{\frac{1}{3}}$ for March and April 2010. Grey lines indicate the 250-m depth contour, used as a mask for the fitted surface. Darker areas indicate higher $\tilde{N}^{\frac{1}{3}}$.

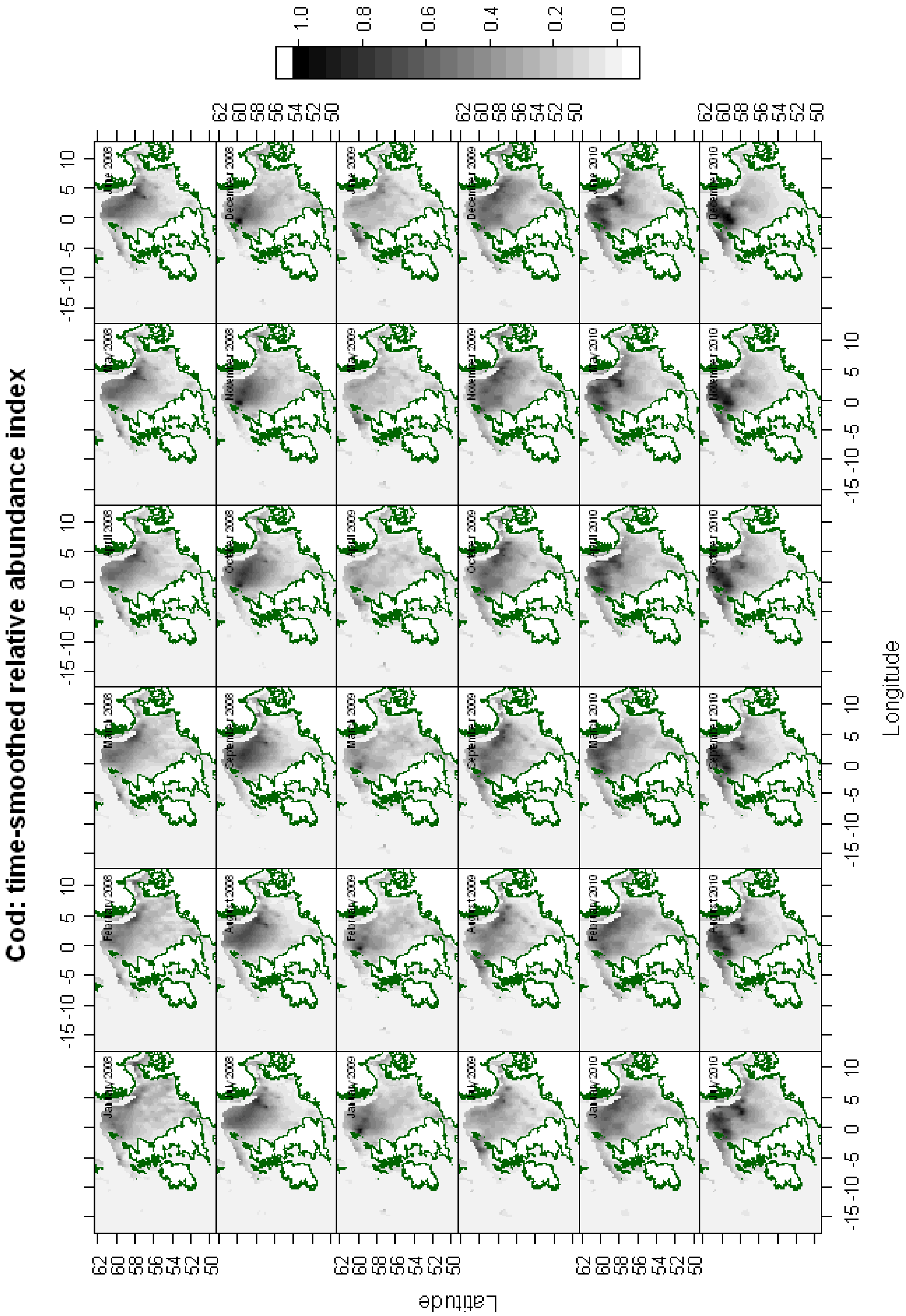


Figure 11.11: Fitted trend surface (with temporal smoothing) for rescaled cod abundance $\tilde{N}^{\frac{1}{3}}$ for all months during 2008-2010. Darker areas indicate higher $\tilde{N}^{\frac{1}{3}}$.

12 Data for analysing fleet dynamics

12.1 INTRODUCTION

In this Section, I consider the Vessel Monitoring System (VMS) and Remote Electronic Monitoring (REM) data that are available for characterising and modelling fleet dynamics in response to measures taken by fisheries managers (in this case, temporary closed areas). VMS data have been used in previous studies of the effects of closed areas, but these have tended to focus on such aspects as descriptions and models of effort distribution in the vicinity of closures (e.g. Murawski et al. 2005), or the potential impacts of effort redistribution from large, permanently closed areas (e.g. Dinmore et al. 2003). REM data have only recently become available, and analyses of fleet dynamics using REM data are as yet mostly still in development.

12.2 VMS DATA

12.2.1 Background

Since 2003, monitoring systems of the VMS type have been installed on Scottish fishing vessels longer than 15 m, ostensibly with two main purposes: to assist in search-and-rescue operations, and to enable Compliance officials to know where a vessel was at a given time (and therefore whether it was transgressing in closed areas, for example). VMS is in widespread use: all EU, Faroese and Norwegian vessels greater than 15 m in length must be fitted with the system, and from 2012 the minimum length for EU vessels will change to 12 m. The potential value of VMS data to scientists studying fleet behaviour and producing stock assessments was clear immediately, but permission for Scottish fishery scientists to access VMS data was granted by the Scottish fishing industry only in 2007 (Gatt and Reid 2007). Since then, scientists from government laboratories have been allowed to use such data for research purposes. However, such access is limited to studies concerning the Common Fisheries Policy (CFP) of the EU and associated issues. Issues arising from access restrictions and dissemination are discussed in Section 12.2.2.

VMS data consist of vessel speeds, headings, and locations, with one reading (known as a "ping") being transmitted to a central repository via a satellite link every 2 hours. The data are actually generated at a much higher frequency (as much as once every 10 seconds), but the limitation to one ping every 2 hours reduces the cost of satellite transmissions. Even at this frequency, there are often periods of missing data in the VMS database; these can occur for various reasons, principally faulty equipment.

The database used for this study contains VMS records for all Scottish demersal vessels (>15 m) fishing during 2008 to 2010. Each record consists of the following fields:

X Unique identifier for the VMS ping.

Vessel.Id The identifying number the vessel in the VMS database.

Logtime The time and date of the VMS record, in a YYYY-MM-DD HH:MM:SS format (for example, `2008-01-02 18:33:00`).

Latitude and Longitude Expressed as decimal degrees from the equator and the Greenwich meridian.

Knots.SUM The inferred speed of the vessel at the time the ping p_t was sent. This is estimated by considering the distance moved and the recorded time of the previous ping p_{t-1} and the subsequent ping p_{t+1}.

PLN The Port Letter Number for the vessel. This identifies the port (or other relevant authority) with which the vessel is registered, along with an identifying number for the vessel itself. It does not follow, however, that a vessel registered to a Scottish port must be Scottish, so the PLN is not necessarily a useful guide to nationality.

COD, HAD, WHG, MEG, MON, POK, PLE, NEP, MAC, HER, WHB, SCE, CRE, CRS, LOB The VMS data records transmitted by each vessel do not include information on fish catches. However, when collating VMS datasets for analysis, Marine Scotland staff combine VMS data with sales notes and data on reported landings held in Marine Scotland's Fisheries Information Network (FIN) database. These fields give the total landed yield (in kilograms), for the trip as a whole (so every VMS ping in a given trip will have the same value of COD, say), and I have used the data in Section 14 to determine which vessels to include in the time-series VMS analysis. The species recorded are cod, haddock, whiting, megrim, monkfish, saithe, plaice, *Nephrops*, mackerel, herring, blue whiting, common scallop, edible crab, swimcrab and lobster.

Trip.Id The identifier for the trip in the VMS database.

Gear.Code A code (taken from FIN) indicating the gear used for the given trip. The full list of codes (and therefore the full list of fishing gears and methods used in Scotland) is given in Table 12.1.

Mesh.Size The mesh size (where relevant) of the net used for the given trip.

RSS Following the UK Merchant Shipping (Registration, etc) Act of 1993, all commercial fishing vessels must be registered with the Registry of Shipping and Seamen (RSS); see also the Scottish Government website at `http://www.scotland.gov.uk/Topics/marine/Licensing/`. The RSS number is a unique identifier for the vessel and does not change with new skippers or owners.

12.2.2 Public dissemination of VMS data

Before using VMS data in fleet analysis, I note that general dissemination and transmission of VMS data to the public are not permitted. The Freedom of Information Scotland Act (2002) does not apply, because VMS data are considered to be sensitive personal data and are separately protected under EU law. However, it is important to note what are and are not thought of as VMS data. This term is intended to cover data on the vessel identity, speed, position and heading of individual vessels. Recent legal advice (Scottish Government, *pers. comm.*, 2011) indicates that suitably-anonymised *plots* of vessel position and speed are not VMS data, and can be included in publically-available documents (including doctoral theses). A more recent interpretation (P. Degnbol, ICES, Copenhagen, *pers. comm.*, 2011) of the EC Data Collection Framework and Implementation Regulations (European Commission 2008) goes further in concluding that all such data are "in practice public domain with a few limitations." However, the legal position has not yet been fully clarified or tested, and it is not yet clear which of these two interpretations (if either) is correct.

In this context, it is important to be able to generate plots which summarise a vessel's position and speed in a way that does not permit the determination of the identity or exact fishing locations of the vessel, as this is commercially-sensitive information that it would be illegal to present. This is not a significant issue if, for example, the plot shows the aggregated VMS pings for an anonymous vessel over a quarter or a longer time period, but it does become problematic if the requirement is to present VMS pings for a specific trip undertaken by that vessel. Standard plots of VMS positions are not appropriate for this purpose, so several alternatives were tested. Note that the results given here (Figures 12.1 to 12.3) are *not* to be considered as part of the VMS analyses presented later in this Chapter: they are intended only to illustrate an alternative way of displaying VMS data that does not impinge on commercial confidentiality.

The first stage of the test was to generate simulated VMS data. This had to represent a trip path with varying speeds and headings, arranged so that one or more discrete fishing areas could be determined (as is characteristic of actual VMS data). Suppose I want to generate a path with 100 VMS-type "pings" (so that $n = 100$). Given a position (x_t, y_t) at time t, movement during the period t to $t+1$ can be determined by a vector $\mathbf{v}_{t+1}$ with length (or speed)

$$\phi_{t+1} = 10\left[\sin\left(\frac{10t}{n}\right) + 1\right] \tag{12.1}$$

and angle

$$\theta_{t+1} = T\theta_t + \varepsilon_t, \tag{12.2}$$

so that θ can be considered as an ARMA(1,0) process with autoregressive term T and variation $\varepsilon \sim N(0, 0.75)$. The position at time $t+1$ is then given by

$$x_{t+1} = \phi_{t+1}\cos(\theta_{t+1}) \tag{12.3}$$

$$y_{t+1} = \phi_{t+1}\sin(\theta_{t+1}) \tag{12.4}$$

Any t at which $\phi_t < 15$ was considered to represent fishing activity. Figure 12.1 illustrates a time-series of ϕ and θ for one particular realisation of this simulation scheme, while Figure 12.2 shows the equivalent VMS-type pings. The pattern produced is typical of what would be expected to be seen in real VMS data from a fishing trip, with relatively discrete fishing areas separated by steaming activity. Finally, Figure 12.3 summarises the application of a simple ping-binning technique to these simulated data: this relates the colour used to shade a map square to the density of VMS pings within that square. The most suitable output format (given in the lower right subplot of Figure 12.3) indicates the locations of fishing and non-fishing activity in broad terms, without permitting the precise identification of trawl locations, and is appropriate for the analyses of vessel movement response presented in the remainder of this Chapter. It should be noted, however, that the actual VMS ping locations are retained in the dataset and are used in the analyses considered here, so accuracy has not been sacrificed.

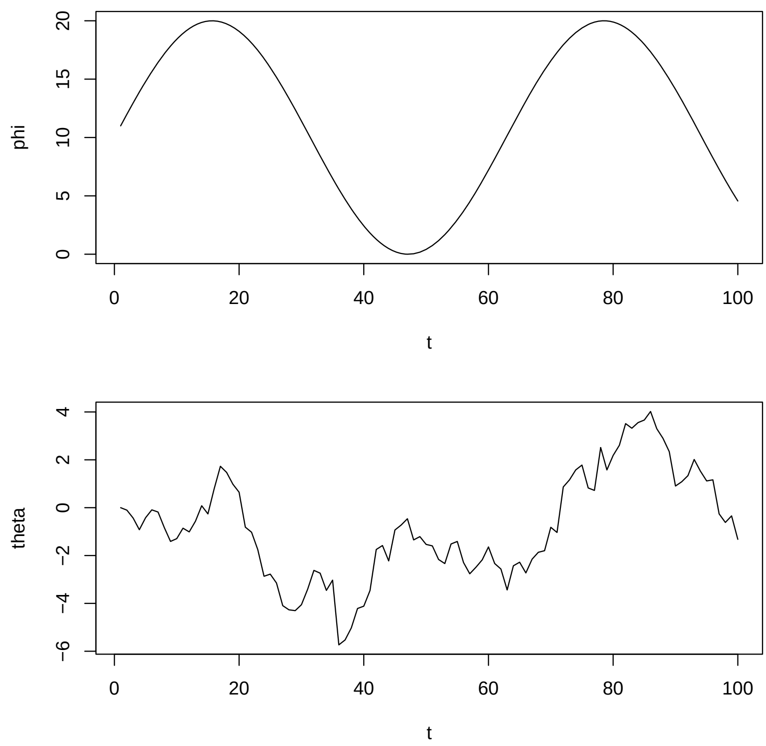


Figure 12.1: Time-series of ϕ (upper) and θ (lower) for one realisation of a simulated fishing trip.

Code	Description	Code	Description
DRB	Boat dredge	LNS	Shore operated stationary lift nets
DRH	Hand dredge	LTL	Trolling lines
FAR	Aerial nets	LX	Hooks and lines (not specified)
FCN	Cast nets	MIS	Other miscellaneous gears
FG	Falling gear (unspecified)	OT	Otter trawls (not specified)
FIX	Traps (not specified)	OTB	B trawls otter (side/stern not specified)
FPN	Stationary uncovered poundnets	OTB1	B trawls otter trawls (side)
FPO	Covered pots (creels)	OTB2	B trawls otter trawls (stern)
FSN	Stownets	OTM	Mid trawls otter (side/stern not spec)
FWR	Barriers, fences weirs, etc	OTM1	Mid trawls otter trawls (side)
FYK	Fyke nets	OTM2	Mid trawls otter trawls (stern)
GEN	Gill/entangling nets (not specified)	OTT	Twin trawls Otter twin multi trawls
GN	Gill nets (not specified)	PS	Purse seine
GNC	Encircling gillnets	PS1	Purse seine operated by one vessel
GND	Drift gillnets	PS2	Purse seine operated by two vessels
GNF	Fixed gillnets (on stakes)	PT	Pair trawls (two vessels) not specified
GNS	Set gillnets (anchored)	PTB	B trawls pair trawls (two vessels)
GTN	Combined gillnets-trammel nets	PTM	Mid trawls pair trawls (two vessels)
GTR	Trammel nets	SB	Beach seines
HAR	Harpoon	SDN	Boat/vessel seines-Danish seines
HMD	Mechanized dredges	SFH	Shell fishing by hand
HMP	Pumps	SPR	Boat/vessel Pair seines(two vessels)
HMX	Harvesting machines(not specified)	SSC	Boat/vessel seines-Scottish seines
LA	Without purse lines (lampara)	SX	Seine nets (not specified)
LHM	Handlines and polelines (mechanised)	TB	B trawls bottom trawls (not specified)
LHP	Handlines and polelines (hand-operated)	TBB	B trawls Beam trawls
LL	Longlines (not specified)	TBN	B trawls nephrops trawls
LLD	Drift longlines	TBNT	Twin trawls nephrops twin muli trawls
LLS	Set longlines	TBS	B trawls shrimp trawls
LN	Lift nets not specified	TM	Mid trawls (not specified)
LNB	Boat operated lift nets	TMS	Mid trawls shrimp trawls
LNP	Portable lift nets	TX	Other trawls (not specified)

Table 12.1: Scottish fishing gear and method codes used in VMS data, and in Marine Scotland's Fisheries Information Network (FIN).

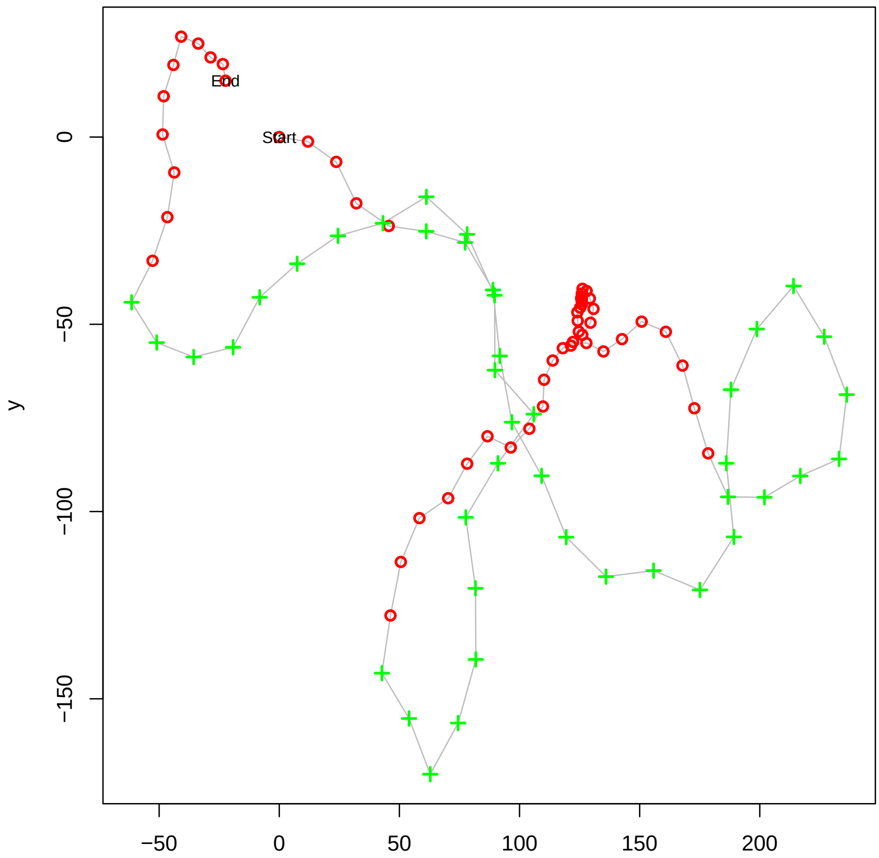


Figure 12.2: VMS-type pings for a simulated fishing trip path generated by the ϕ and θ time series given in Figure 12.1. Fishing locations ($\phi < 15$) are indicated in red, steaming locations in green.

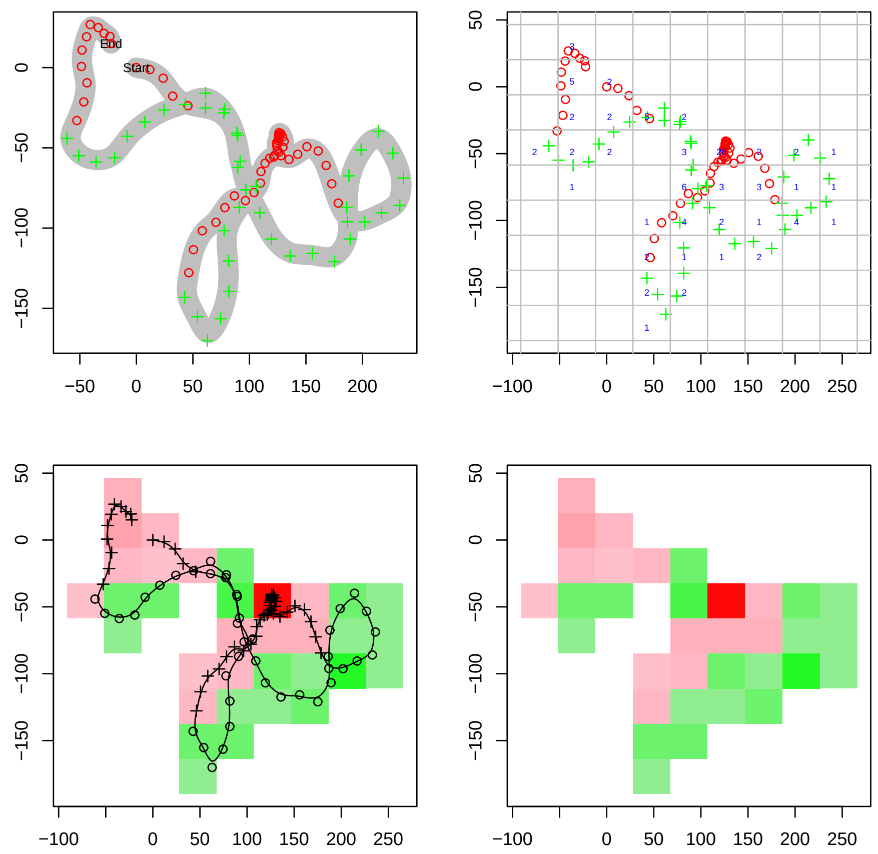


Figure 12.3: Summary of an aggregation procedure for VMS data from a single trip. Upper left: simulated fishing (red) and non-fishing (green) VMS pings, with an overlaid spline path. Upper right: subdivisions of the area into equal aggregation bins, with VMS pings and counts of the number of pings in each bin (blue numbers). Lower left: aggregation bins shaded by ping abundance (darker colours indicate more pings), with overlaid VMS pings and path. Note that only fishing pings are included in the scaling for those bins with both fishing and non-fishing pings. Lower right: final VMS summary.

12.3 REM DATA

12.3.1 Background

REM equipment was first used in Europe for compliance and science purposes on Danish fishing vessels in 2008. In that year, the European Commission offered member states the option to acquire additional North Sea cod quota for some of their vessels (European Commission 2010), if it could be demonstrated that these vessels had made successful efforts to reduce their *catches* of cod (rather than reducing landings as had been the case previously). The Danish government concluded that the best way to effect such a demonstration was to install monitoring equipment on fishing vessels that would enable fishery officers to determine what had been caught, where it had been caught, and which gear had been used to do so.

The initial pilot project was run during 2008 (Dalskov and Kindt-Larsen 2009, Kindt-Larsen et al. 2011). Seven systems were installed on Danish fishing vessels, provided by Archipelago Marine Research Ltd., Victoria, British Columbia, Canada (see `www.archipelago.ca`). Archipelago has provided similar fishery monitoring services in Canada for over 30 years. Each system consists of a number of units:

- A stand-alone PC which acts as a control unit, and to which all other components are connected.
- A removable hard drive (capacity 500 Gb to 1 Tb) which stores video and data files and allows them to be easily transported to a central point for analysis and interpretation.
- A number of video cameras, robustly mounted in waterproof housings. In the Danish trials, up to four cameras were installed on each vessel. The positions of the cameras varied from vessel to vessel and were strongly dependent on the fishing and catch-processing procedures used by the vessel, but generally included views of:
  - The location where the net was drawn up onto the vessel (the stern for many trawlers, but other points where relevant for different vessels);
  - The point at which the catch was loaded into the fish house;
  - The main catch-sorting area (or belt if installed);
  - The route by which discards were returned to the sea.
- A voltage meter to indicate the power supply to the REM systems, which could be intermittent and cause system failure on some smaller vessels.

- A counter indicating the number of net drum rotations per minute.
- A sensor measuring the hydraulic pressure (psi) in the winch mechanism. This will return a high (vessel-dependent) value whenever the net is in the water: both this and the drum-rotation counter can be used to indicate when the net is being set and when it is being hauled. The resultant data may overestimate slightly the length of time for which the vessel is actively fishing, as a demersal net (for example) does not generally start working until near the sea bed. However, the extent of any such overestimation cannot be measured without data on net geometry and position that are not readily available.
- A standard GPS system indicating the position, heading and speed of the vessel.

Once installed, the systems were put into operation on a number of Danish fishing trips thought to be representative of the fishing effort for the vessels concerned, and methods were developed to analyse and interpret the resultant wealth of video and sensor data.

The Danish trials were deemed to be a success (Dalskov and Kindt-Larsen 2009, Kindt-Larsen et al. 2011) and further trials were planned for 2010 and 2011. Component systems were subsequently purchased by the Scottish, English, German, Dutch and Swedish governments, all intending to use their systems in slightly different ways but all with the underlying (though sometimes unstated) goal of accessing additional cod quota for their vessels. Some of this purchasing may be considered to have been a little premature: the positive results of the Danish trial related only to discards of cod, and several governments (particularly Scotland) have very ambitious plans to use REM systems for a number of compliance and science purposes. However, the full utility of an REM system for tasks such as discard species composition and biological sampling has yet to be determined at the time of writing. I am leading on REM research at the Marine Laboratory in Aberdeen, and at the time of writing I am closely involved in a number of REM projects that have generated widespread media interest (see, for example, Lindsay 2011).

12.3.2 Determining fishing activity through VMS and REM data

Despite the issues raised in the previous Section, the benefits of REM sensor data remain clear. Unlike VMS location and speed data, which is broadcast (under current regulations) every two hours, REM data are stored every ten seconds. It is also possible to determine very precisely whether a vessel is actually fishing in a particular location or not, using the combination of video and sensor data. It has therefore become possible to test the commonly-used assumption (e.g. Borchers and Reid 2008, Vermard et al. 2010) that a trawler moving at $4\frac{1}{2}$ to 5 knots or less must be fishing.

To demonstrate this, I compared REM and VMS data for one trip of a particular Scottish demersal whitefish trawler fishing during 2009. Due to the commercially-sensitive nature of these data, it would be inappropriate to name the vessel: I will refer to it as Vessel A. REM sensor data were downloaded from the hard-drive data generated during the relevant Scottish REM trials (Marine Scotland 2010). VMS data were taken from the Scottish Government FIN database generated for the project described in Section 13.2 below. The drum-rotation counter had not been working on this particular trip, so the principal source of information regarding fishing activity was the winch-pressure sensor. The winch operates continually while the net is in the water, in order to maintain contact with the seabed (or to maintain the net at a constant depth), so the winch sensor provides a direct measure of activity. Full camera coverage was also available, but not used in this analysis.

The winch pressure levels that signify when the winch is or is not being used vary from vessel to vessel, so the first task was to determine what these levels were for Vessel A. Figure 12.4 (upper plot) reproduces the winch pressure readings for the whole trip. These are highly variable, and to facilitate interpretation a loess curve (span = 0.01) was fitted through the observations. The lower plot of Figure 12.4 gives the frequency distribution of the fitted loess curve points. The distribution was split into two sub-distributions at its minimum (which I denote by P_{split}), and the maxima of both subsections were determined. These maxima were denoted by P_{off} and P_{on} for the left and right sub-distributions respectively, and indicate the modal winch pressure for "fishing" (when the winch is working; P_{on}) and "not fishing" (for when it is not; P_{off}). For Vessel A:

$$\begin{aligned} P_{\text{off}} &= 12.22 \\ P_{\text{split}} &= 388.12 \\ P_{\text{on}} &= 1338.54 \end{aligned}$$

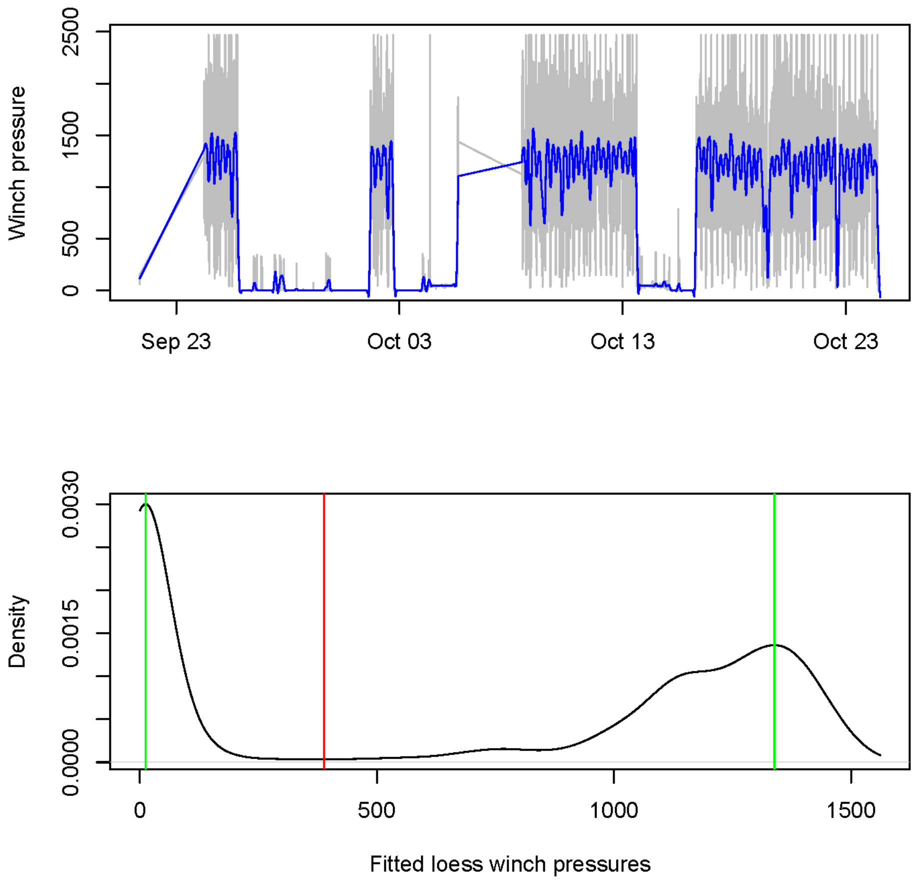


Figure 12.4: Upper plot: REM winch pressure (psi) time series from Vessel A (grey line) with fitted loess curve (blue line). Lower plot: frequency distribution of fitted loess curve values from upper plot. The red vertical line indicates the minimum P_{split} of the distribution, while the green vertical lines (P_{off} and P_{on}) give the maxima of the sub-distributions formed by partitioning the full distribution at the minimum.

Each day of data from the time-series for Vessel A was analysed separately, and the results combined to allow conclusions for the time-series as a whole. Figure 12.5 summarises the available information from Day 1 of the time-series. The correlation between REM and VMS speed measures appears to be quite poor ($R^2 = 17.35\%$), although the REM speed data are very variable and a direct correspondence with the VMS speed data is not always evident. For example, the average speed comparison R^2 over all days from Vessel A for which both VMS and REM data are available is only 63.62%.

REM winch pressure data for each day were categorised as follows. To reduce the effect of high variability in pressure data, a loess curve P_{loess} was fit to the raw winch pressure time series for each day, using local polynomial regression fitting and a small span (0.05). Each point on P_{loess} was then categorised as fishing or not fishing by comparison with the estimated split value $\left(P_{\text{split}}\right)$ calculated via Figure 12.4: all times for which $P_{\text{loess}} \geq P_{\text{split}}$ were deemed to be fishing times, otherwise the vessel was assumed to be not fishing. The resultant time series are indicated in Figure 12.5 (lower left subplot): this suggests good agreement between the REM-derived indicator of fishing activity and the VMS speed-derived indicator, save for two points in mid-morning and late evening when the VMS speed was greater than 5 knots but the REM winch pressure indicated fishing activity. These points are also highlighted in the contingency table plot of VMS speed against REM loess winch pressure (lower right subplot of Figure 12.5), with both appearing in the upper-right quadrant (indicating disagreement between the two measures). For Day 1, VMS and REM fishing indicators agree for 8 (88.9%) out of 9 available time points.

Figure 12.6 shows the equivalent comparison for Day 2, for most of which Vessel A was fishing before steaming for the mainland in the evening. The correlation between REM and VMS speed data is good for this day (94.56%), as is the agreement between REM and VMS fishing indicators (12 out of 14 points, or 85.7%). A comparison is not always possible, however. Figure 12.7 is an example of a day for which VMS data are not available. The reasons for the lack of VMS data are not known, but some VMS data were absent on 11 out of 31 days in the time-series.

Summing the daily contingency tables comparing REM and VMS fishing indicators results in the following overall contingency table.

	REM not fishing	REM fishing
VMS not fishing	90	7
VMS fishing	7	117

In other words, over the full time-series REM and VMS fishing indicators agreed for 207 out of 221 time points (93.7%). A simple χ^2 test applied to the table above indicates strong support ($p < 2.2e - 16$) for the hypothesis that the measures are not independent.

I can also determine *how* dependent they are in a statistical sense. I assume firstly that the REM indicator of fishing is the correct baseline value, against which I am testing whether the VMS indicator of fishing agrees. Define a binomial variable F_{rem}, such that

$$F_{\text{rem}} = 1 \quad \Rightarrow \quad \text{Fishing according to REM winch data}$$
$$F_{\text{rem}} = 0 \quad \Rightarrow \quad \text{Not fishing according to REM winch data}$$

Define a second variable F_{agree}, such that

$$F_{\text{agree}} = 1 \quad \Rightarrow \quad \text{REM and VMS indicators agree}$$
$$F_{\text{agree}} = 0 \quad \Rightarrow \quad \text{REM and VMS indicators disagree}$$

I then fit the following GLM to these data, using a binomial fit function with a logit link:

$$F_{\text{agree}} \sim F_{\text{rem}} - 1. \tag{12.5}$$

This will produce estimates for two factors, one for when REM and VMS both indicate fishing, the other for when they both indicate no fishing. These factors will be expressed on the logit scale. Converting back to the arithmetic scale and estimating 95% confidence limits (CLs) yields

Factor	Lower CL (2.5%)	Estimate	Upper CL (97.5%)	p-value
VMS and REM indicate fishing	0.8651	0.9278	0.9683	7.58e-11
VMS and REM indicate no fishing	0.8937	0.9435	0.9753	4.56e-13

In other words: if REM indicates fishing, VMS also indicates fishing for around 93% of the observations, with a confidence interval of 87% to 97%. If REM indicates no fishing, VMS agrees for 94% of such occasions, with a confidence interval of 89% to 98%. Both factors are strongly significant. The factor estimates can be obtained directly from the contingency table above, but the GLM is required to evaluate significance and obtain confidence intervals.

Hence, if I assume that REM winch-pressure data accurately indicates fishing activity, then VMS speed data is a reasonably good proxy which agrees with REM indicators on over 90% of observations (for this trip of Vessel A). This supports the use of VMS data as a marker of fishing activity, as suggested by Borchers and Reid (2008) and Vermard et al. (2010), and implemented in recent years by enforcement authorities in Scotland and elsewhere. The assumption that a vessel for which VMS data indicate a speed of less than 5 knots must be fishing is therefore used for the rest of this Chapter.

On a final note: REM data provide one way of interpolating between VMS pings, but another approach is illustrated in Figure 12.8 which shows how confidence intervals about a transit line between pings could be generated. Song et al. (2010) used this idea in a fascinating paper on characterising the movement pattern of people from mobile-phone transmission records, and a similar method could prove very applicable in the future to studies of fishing vessel movements.

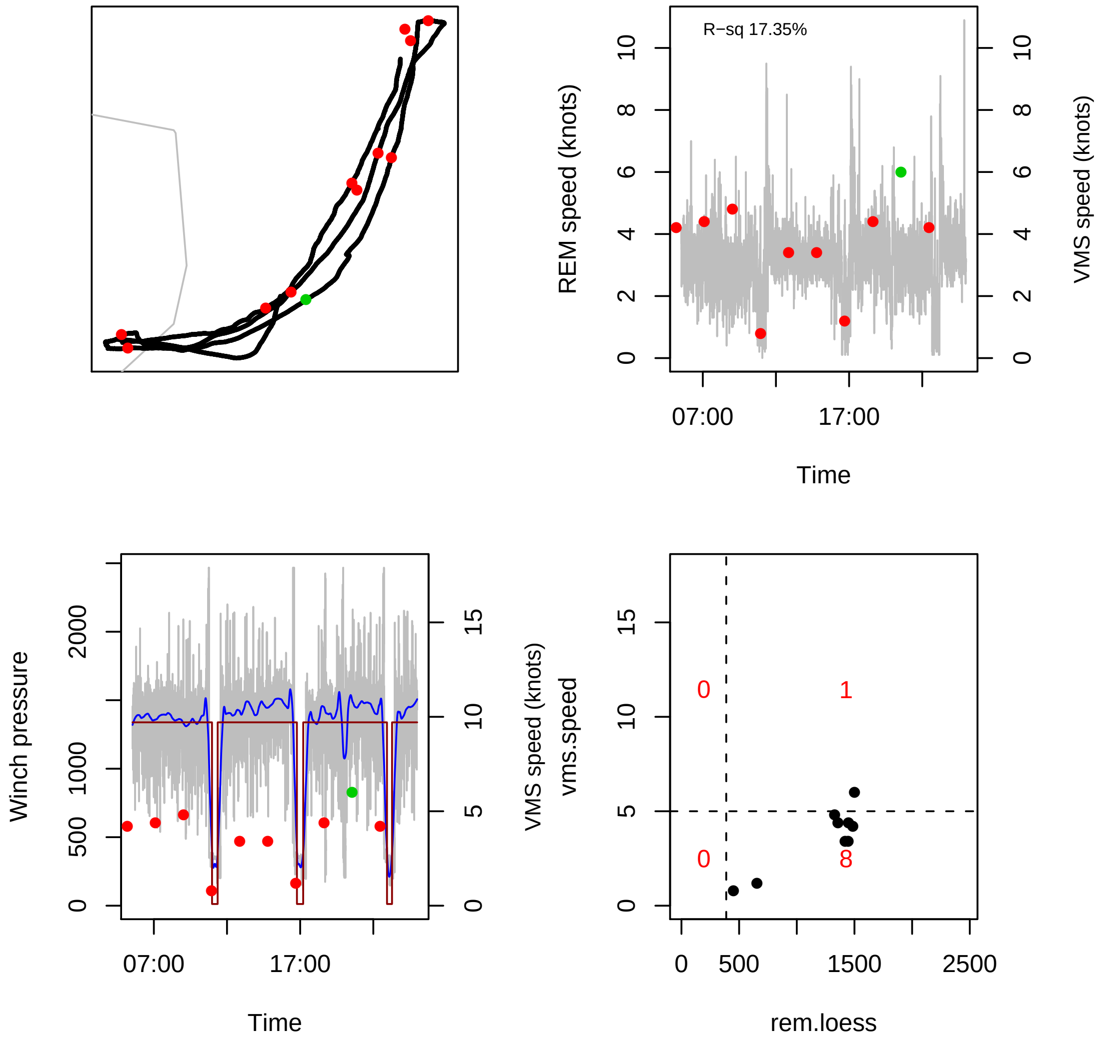


Figure 12.5: Comparison of VMS and REM sensor data for Day 1 of REM time-series from Vessel A. Upper left plot: vessel position. Black line gives REM position data: points give VMS position data, categorised as fishing (red) or not fishing (green). Grey lines show bathymetry contours in 100-m intervals. To ensure anonymity, latitude and longitude axis labels have been removed. Upper right plot: time-series of REM (lines) and VMS (points) speed data, along with the R^2 value from a linear model fit to REM against VMS data. Lower left plot: winch pressure time series (grey line), with loess fit (blue line) and blocked equivalent (red line). VMS speed data (points) are given as before. Lower right plot: scatterplot and contingency table of VMS speed data against the loess fit to REM winch-pressure data. Vertical line is at P_{split}, while horizontal line is at 5 knots. The number of points in each quadrant is also indicated.

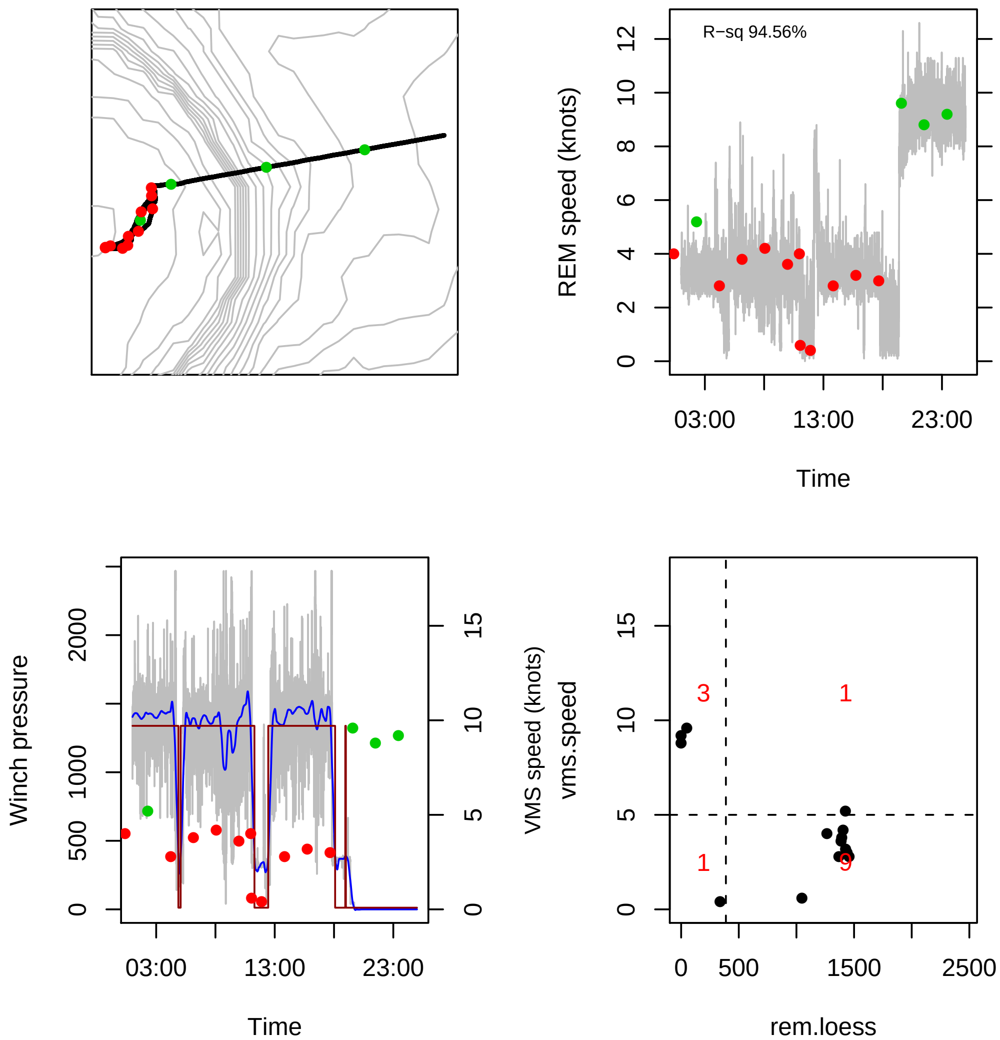


Figure 12.6: Comparison of VMS and REM sensor data for Day 2 of REM time-series from Vessel A. See caption of Figure 12.5 for details.

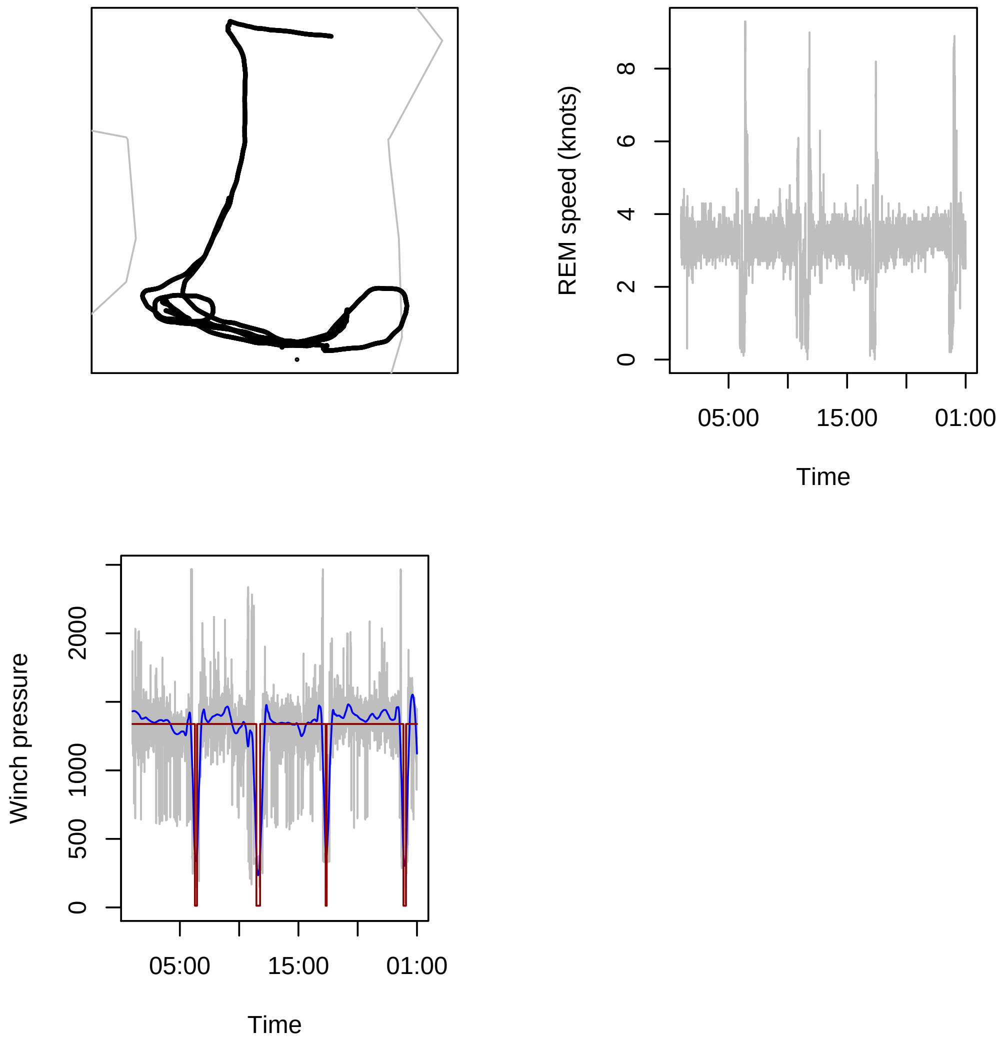


Figure 12.7: Comparison of VMS and REM sensor data for Day 17 of REM time-series from Vessel A. See caption of Figure 12.5 for details.

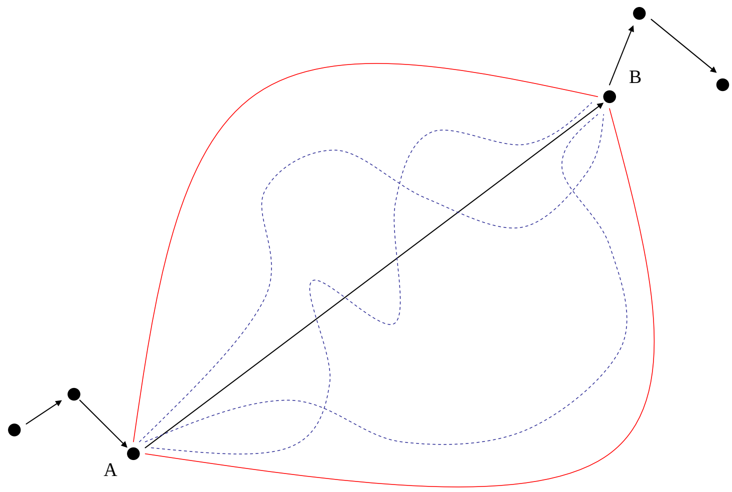


Figure 12.8: Conceptual model of path uncertainty between two VMS pings A and B. The black line shows the direct path, which is generally assumed to be the route taken. Blue lines give examples of paths that the vessel *could* have taken in the time available to get from A to B, while red lines show possible confidence bounds about the hypothesised route which could be generated from consideration of many possible paths.

13 Fleet responses to real time closures

13.1 The Scottish Real Time Closure (RTC) scheme

As part of its Conservation Credits initiative which began in 2008, the Scottish Government instigated a series of RTCs intended to divert demersal fishing effort away from areas of abundant cod, and thereby reduce cod mortality. The RTCs were stipulated as areas of approximately 50 square nautical miles, and were initially defined as 7×7 nautical-mile squares, although this limitation was subsequently relaxed and RTCs may now be of different shapes. Following analyses which suggested that the residence time of cod in a 7×7 square nautical mile area could be less than three weeks (Peter Wright, Marine Scotland Science, Aberdeen, *pers comm*), the maximum possible area of each RTC since June 2010 has been increased to 225 square nautical miles. Each RTC is in place for 21 days, following which period they are automatically reopened. Further, rules limit the number of RTCs that can be enacted simultaneously in close proximity, in order to prevent local fishing communities being unfairly disadvantaged. The closure of an area is triggered by an upper limit on the observed cod density, defined as 40 cod (of any size) per hour's fishing. Notification is via skipper's logbooks, monitored landings, or by on-board observation, and a single high-density haul is sufficient to instigate a closure. There may only be a maximum of 11 closures defined by logbook or landings data in operation at any one time, along with an additional three closures defined by positive on-board samples. Since 2009, observance of RTCs by Scottish demersal fishing vessels has been mandatory. There is no legal impediment to vessels from other countries fishing in RTCs, although they have been encouraged by the Scottish Government and the EU not to do so, and anecdotal evidence from compliance officers and the Scottish fishing industry suggests that RTCs have generally been respected by non-Scottish vessels.

Full details on how RTCs are defined within the Conservation Credits scheme are given in Holmes et al. (2009): see also European Parliament (2010). In all, 15 such closures were implemented in 2008. An expansion of the scheme led to 144 closures in 2009 (Figure 13.1), 165 in 2010 (Figure 13.2), and 142 in 2011 (as of 5th October). Although the area covered by the closures in 2009 and 2010 looks substantial, it is important to note that only a few of the RTCs were in force on any given day: Figure 13.2 also shows the extant closures on 1st July 2010.

In the Section, I will analyse the movement response of Scottish vessels to RTCs, as shown by VMS data. The analysis considers vessels moving away from RTCs when closed, vessels fishing in (or very near to) RTCs while they are closed, and vessels returning to the area of RTCs after reopening. The response metrics are the difference in the mean RFII of subsequent trips (see Section 13.2) and the distance moved. The analysis will go part of the way towards characterising such reponses, and it is my intention that the results will ultimately be reflected in the development of (and the output from) spatial response models of the kind discussed in Chapter IV.

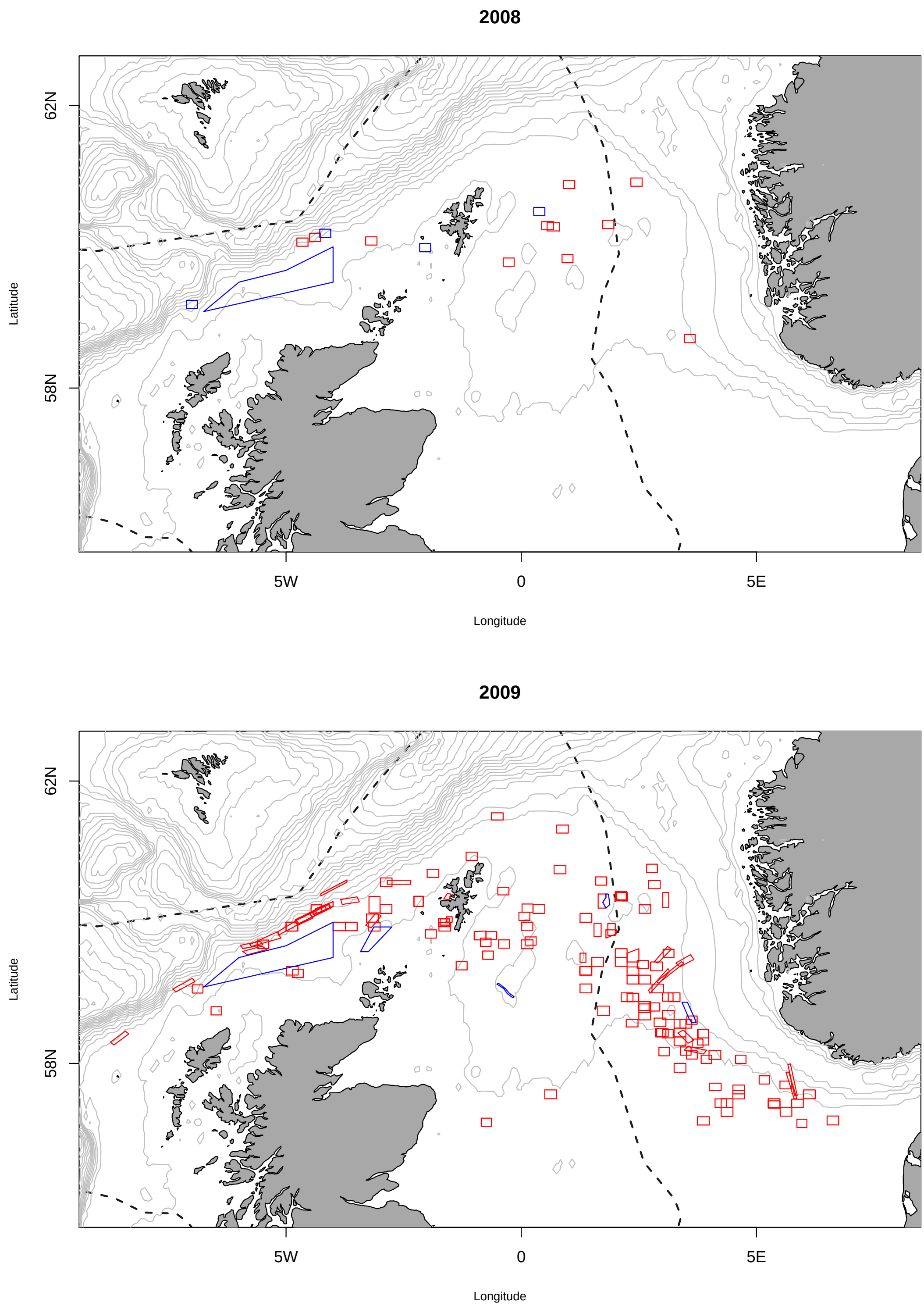


Figure 13.1: Real-time closures (RTCs; red) and permanent or other seasonal closures (blue) implemented by the Scottish Government in 2008 (upper) and 2009 (lower). The dotted line shows the extent of the UK EEZ, and grey lines show bathymetry at 100-m intervals.

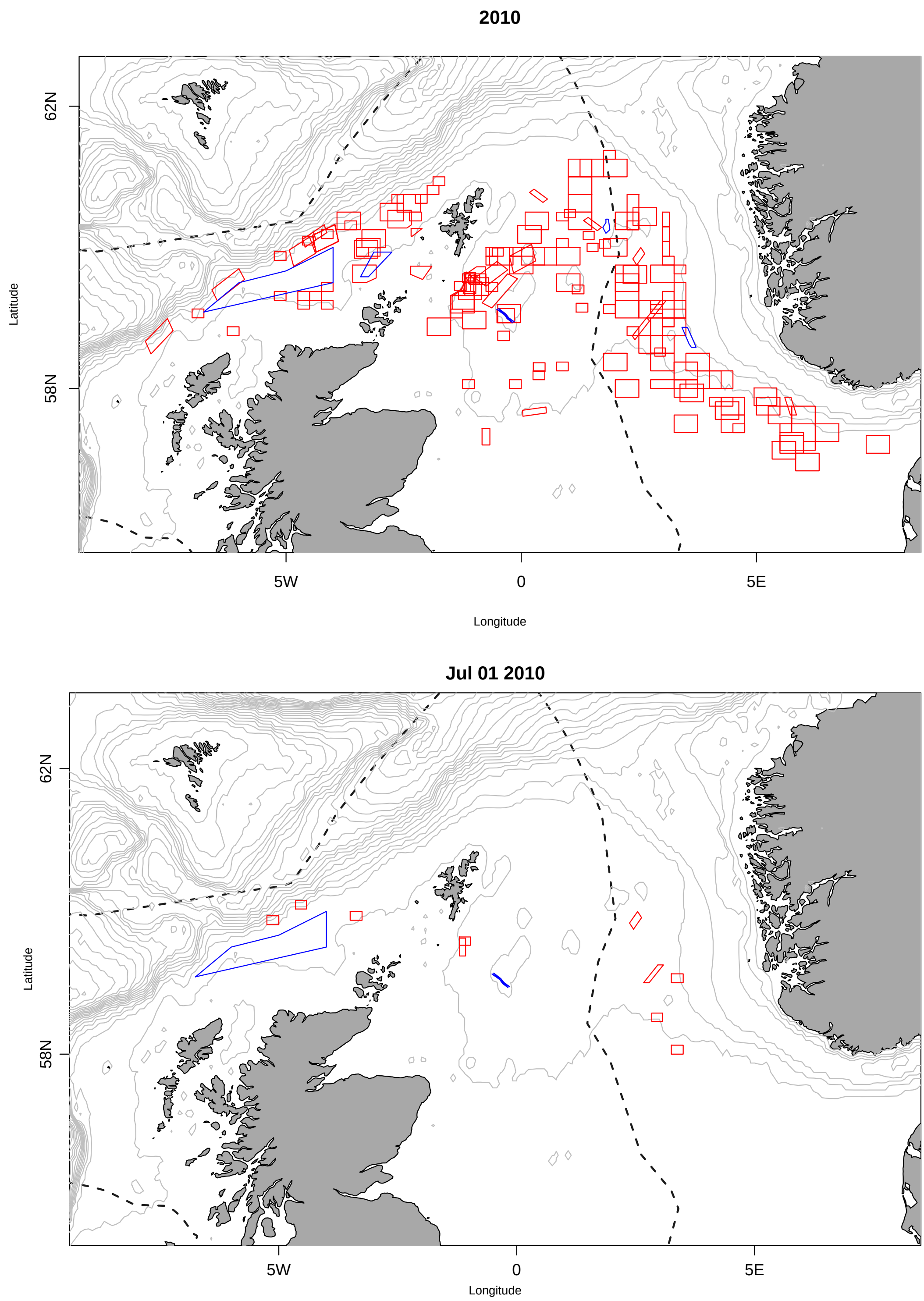


Figure 13.2: Real-time closures (RTCs; red) and permanent or other seasonal closures (blue) implemented by the Scottish Government in 2010 (upper), and those in place on 1st July 2010 (lower). The dotted line shows the extent of the UK EEZ, and grey lines show bathymetry at 100-m intervals.

13.2 Generation of RFII difference metrics and distances moved

Given a spatio-temporal RFII for cod (see Section 11.2), the next task is to determine those vessels which would be expected to be directly affected by RTCs. The full VMS dataset for 2008-2010 was partitioned by vessel. The VMS data for each vessel were then examined to determine if:

A: the vessel had been fishing within an RTC area during the 15 days preceding closure;

B: the vessel had been fishing in an RTC during the closure;

C: the vessel had returned and fished in the RTC area during the 15 days following reopening.

For each trip in which one of these criteria was met, the mean RFII for all VMS fishing ping locations during the trip was calculated. For cases A and B, the mean fishing-ping RFII for the following trip undertaken by the vessel was calculated; for case C, the mean fishing-ping RFII for the preceding trip was calculated. The mean RFII for the trip of interest was then compared with that from either the preceding or the following trip (the comparison trip), as appropriate. If the mean RFII for the trip of interest exceeded that for the comparison trip, it would indicate that the vessel had moved to an area of less importance for that fish stock following the closure (cases A or B) or reopening (case C), although I cannot conclude that the closure was necessarily the reason for the move: these analyses can only be indicative.

To characterise the location of each fishing trip, I calculated the geographic midpoint $G = (G_x, G_y)$ of all the fishing pings $PF = (PF_x, PF_y)$ for trip t of vessel X, and for the comparison trip $t+1$ (case A or B) or $t-1$ (case C), using

$$G_x = \text{median}\,(PF_x) \tag{13.1}$$

$$G_y = \text{median}\,(PF_y) \tag{13.2}$$

I also performed a cluster analysis on fishing pings for each trip to determine whether the assumption of one geographic midpoint for each trip was valid. Clustering was carried out by partitioning around medoids (Kaufman and Rousseeuw 2005, see also page 177 below), using the PAM function of the `cluster` package (version 1.11.11) in R (version 2.8.1). The results were summarised by a plot of the principal components of the ping data with the suggested number of clusters (k) indicated by ellipses (Pison et al. 1999). For this plot (known as a *clusplot*), the following procedure was carried out:

1. As part of the PAM algorithm, an $(n \times n)$ dissimilarity matrix of the n VMS pings for trip t was created. This gave the Euclidean distances between the location of each ping and the location of every other ping (see Section 14.2 for more details and discussion).

2. A principal components analysis (PCA) was carried out on the elements of the dissimilarity matrix.

3. The clusplot is then given by plotting every VMS ping on the scales of the first two principal components. The variation explained by the components is also given, and each cluster (as determined by the PAM method) is marked by an ellipse. Finally, lines are drawn joining the central point of the ellipses.

If more than one cluster was identified by this procedure, this suggested that my assumption that a single geographic midpoint could summarise the fishing location for that trip may not have been valid.

Finally, the Haversine distance (Equation 11.3) between the two VMS midpoints was used to approximate the distance moved between the areas fished in the two trips, and therefore how far the vessel had moved following the closure (cases A and B) or the reopening (case C).

13.2.1 Results for Vessel X in 2009

For example, consider the case of a certain vessel (which I'll call Vessel X) fishing in the North Sea. Figures 13.3, 13.4 and 13.5 summarise the VMS data for Vessel X from three successive trips during January 2009. Fishing effort during the first trip in the sequence (which was actually Vessel X's second trip for 2009) was focused on the western edge of the Norwegian Deeps, with some fishing also in the region of the Long Hole seasonal closure; although the cluster analysis returns $k = 1$ (see middle lower plot in Figure 13.3), suggesting that geographic midpoint of the pings is a reasonable summary of the fishing locations for that trip (probably because there are many more pings near the Norwegian Deeps than near the Long Hole). During that first trip, Vessel X fished (according to its VMS pings) in an area which became RTC number 1 (for 2009) during the following week (Figure 13.3). Although it cannot be assumed that it was a report from Vessel X that triggered the closure, it can be concluded that Vessel X was operating in that area. The VMS data from the same vessel's next trip shows that fishing was concentrated in the Shetland area (Figure 13.4). In this case, $k = 3$ from the cluster analysis, suggesting three distinct fishing areas (and indeed the location of the geographic midpoint is almost on Shetland itself). Vessel X's third trip in this sequence went back to the edge of the Norwegian Deeps again (Figure 13.5). The pings for this trip, which were adequately summarised by a single geographic midpoint ($k = 1$), entered into three areas which subsequently (within 15 days) became RTCs, and skirted the edges of three others.

The mean RFII for cod by fishing-ping from the first trip was 0.423, whereas that from the second trip was 0.378, and 0.425 from the third. The median distances between trips were 339 km (from the first trip to the second), and 276 km (from the second trip to the third). So, in summary, Vessel X was fishing in an area that was subsequently closed. It moved a considerable distance on its next trip, and fished in an area which (according to the RFII for cod) was less important for cod. On next trip after that, the vessel moved back to near the area of the first trip, and thereby fished once again in an area of (relatively) high importance for cod.

Without consulting the skipper concerned (if indeed he could recall the trips), the precise reasons for these moves cannot be known. There may have been many good reasons other than the closure for the shift in fishing area. In any case, if the RTC was a factor in moving away from the Norwegian Deeps, it was not a long-lasting one: the vessel returned to that area in the next again trip.

I can also collate the results from the full 2009 year of activity for Vessel X. There were 32 identified trips, the first starting on January 1st and the last starting on December 27th. Fishing activity was spread quite evenly through the year, with between one and three trips per month. Contrary to our assumption of a single geographic midpoint, Vessel X tended to visit multiple fishing areas in each trip, and cluster analysis indicated a single ping cluster ($k = 1$) for only 37.5% of the trips (see Figure 13.6).

It is convenient to summarise each trip by a single point, as this simplifies trip comparisons and enables a second level of cluster analysis on the collection of geographic midpoints from each trip. The use of a single midpoint for each trip may not capture the full spatial distribution of each trip, but it may be appropriate to use it as a first approximation when making large-scale comparisons between trips. Applying the same clustering method to trip centres as I applied to VMS fishing pings for each trip, I can spatially categorise the annual activity for a given vessel. Results are given for Vessel X in 2009, in Figures 13.7 to 13.10. These show that the fishing locations for this vessel during 2009 can be broadly categorised into two main areas: the northern North Sea, and Rockall. The finer distinctions within the North Sea that are clear from Figure 13.10 are rather lost in this analysis, as the differences between the North Sea and Rockall are much greater than those within the North Sea.

Finally for Vessel X, I summarise the type of movement undertaken by the vessel following real-time closures. Figure 13.11 shows the geographic midpoints of each trip, as in Figure 13.10, along with arrows indicating the type, distance and direction of those inter-trip movement which were related to RTCs. In 2009, vessel X had a total of 23 trips in which there was some interaction with one or more of 30 RTCs. There were 43 such interactions: 17 trips in which Vessel X fished in the RTC in the 15 days before it was closed, 6 trips in which the vessel fished in the RTC while it was closed, and 20 in which it returned to RTCs in the 15 days following reopening.

It would have been illegal for Vessel X to undertake fishing operations in an RTC during closure, so the trips in which the VMS data indicate this took place need to be examined more closely. The relevant data are presented in Figure 13.12. In all six cases, the fishing pings lie mostly along the edges of the RTCs. There are at most two fishing pings within each RTC while closed, and it could be argued that these are an artefact of the assumption of fishing activity when VMS pings indicate that the vessel is travelling at less than 5 knots (see Section 12.3.2, in which I showed that VMS data are *good* indicators of fishing activity but not *infallible* ones). There does not appear to be a focus of activity from Vessel X within these RTCs while they were closed.

The differences in the mean RFII for cod for the relevant trips, and the mean distances between them, are summarised for Vessel X in 2009 in Tables 13.1 and 13.2. The mean RFII difference for cod in 2009 is only significantly different from zero for one combination of quarter and RTC-involvement type, namely a significant increase in RFII for cod when Vessel X moved back towards RTCs in quarter 3. There are too few observations of RTC involvement to reach statistically-significant conclusions on whether Vessel X moved towards or away from cod following RTCs in 2009.

	before		during		after	
all	-0.061	(p = 0.2448)	-0.11	(p = 0.2205)	0.017	(p = 0.6426)
q1	-0.208	(p = 0.1324)	NA	(p = NA)	NA	(p = NA)
q2	0.004	(p = 0.8538)	-0.106	(p = 0.676)	0.007	(p = 0.8052)
q3	NA	(p = NA)	NA	(p = NA)	**0.064**	(p = 0.0325)
q4	0.042	(p = 0.5182)	-0.017	(p = 0.7442)	-0.078	(p = 0.5823)

Table 13.1: Differences between mean RFII values for cod for pre- and post-closure trips of Vessel X, for the whole of 2009 and for each quarter thereof (q1-q4), and for each of the three cases (see text for details). "NA" indicates there were not enough relevant observations to calculate a mean. p-values of pairwise Student's t-tests carried out to determine whether mean values are statistically different from zero are given in parenthesis: significant differences (at the 95% level) are shown in bold face.

	before	during	after
all	373.9	381.2	114.8
q1	933.2	1068.1	NA
q2	37.8	502.6	36.0
q3	29.5	56.3	**92.6**
q4	107.9	78.8	226.8

Table 13.2: Means of the median distances (km) moved by Vessel X between consecutive trips around closure periods for cod, for the whole of 2009 and for each quarter thereof (q1-q4), and for the three cases (see text for details). Cases and quarters for which relative RFII indices for cod between fishing grounds were significantly different at the 95% level (see Table 13.1) are marked by bold face.

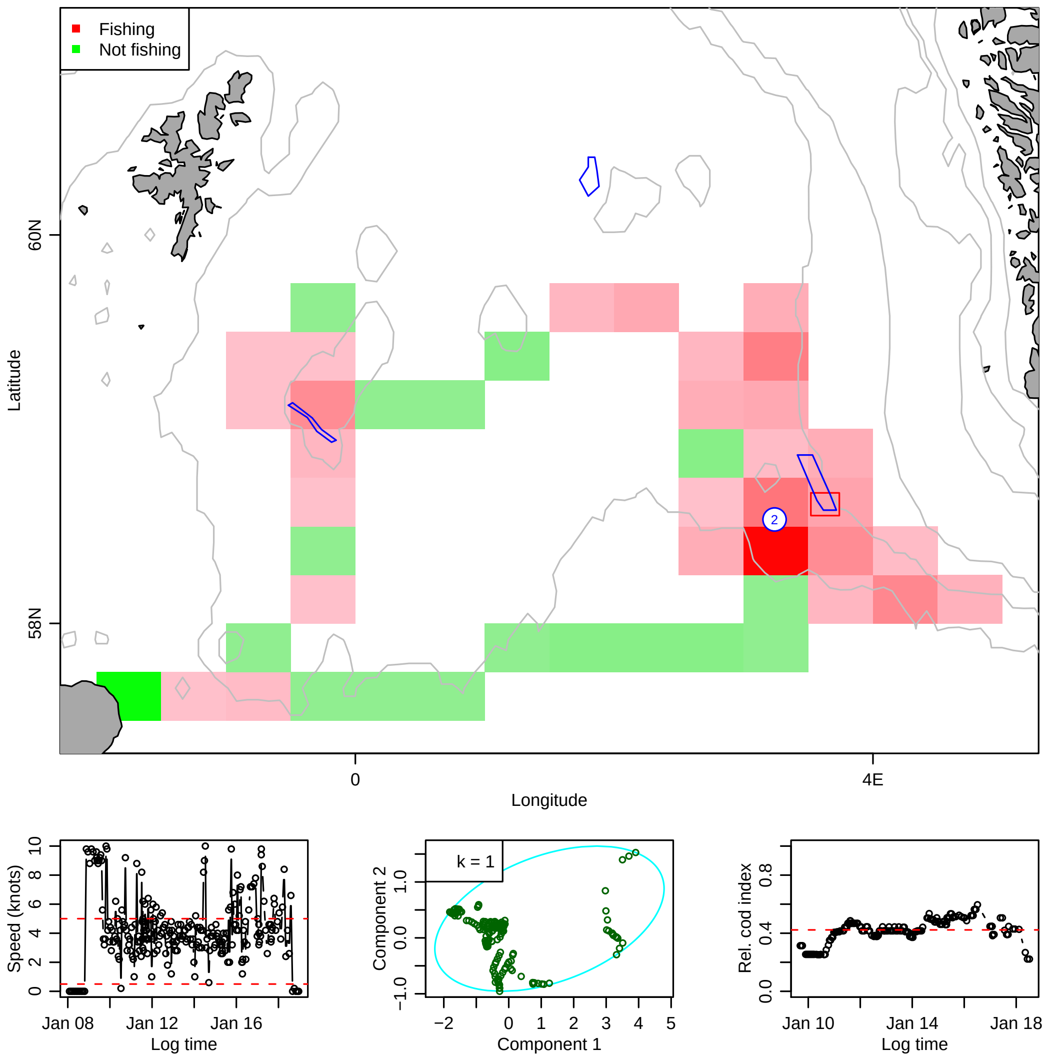


Figure 13.3: Upper plot: aggregation summary of VMS pings for the second trip for 2009 of Vessel X (see Section 12.2.2). Aggregation bins are 0.5° × 0.25° rectangles, shaded by ping density (darker colours indicate more pings). Red shading shows fishing pings, green shading shows non-fishing pings. Note that only fishing pings are included in the shading for those bins with both fishing and non-fishing pings. Red polygons indicate real-time closures; blue polygons show permanent or other seasonal closures. Grey lines show bathymetry at 100-m intervals. The circled number (2) shows the location of the geographic midpoint of the fishing pings for the trip. Lower left plot: time series of the vessel speed estimates (in knots) associated with each VMS ping (fishing and non-fishing). Lower middle plot: principal component plot of fishing-ping cluster analysis (k and the number of ellipses indicate the number of clusters for which there is most evidence). Lower right plot: time-series of estimated RFII for cod at the location of each fishing ping. The dashed red line gives the average for the trip.

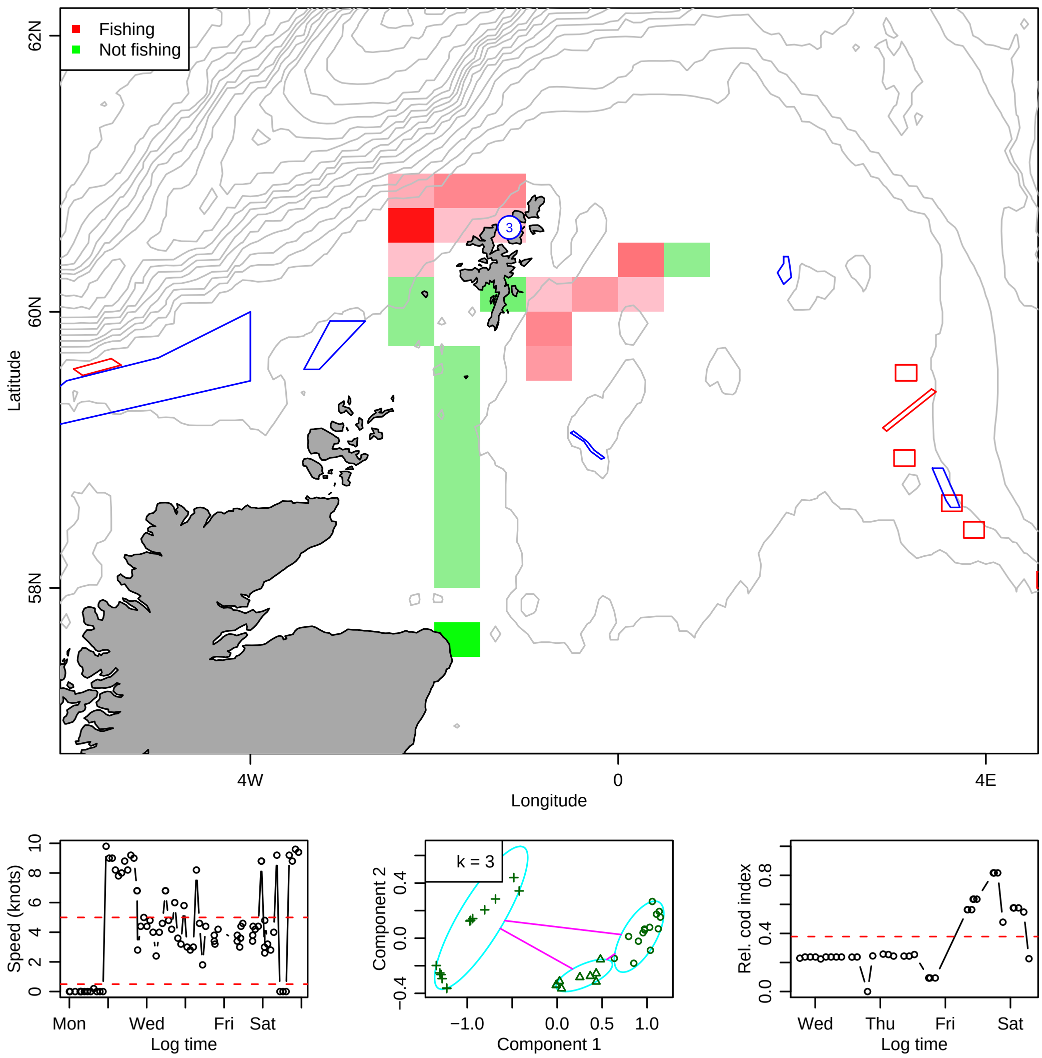


Figure 13.4: Summary of VMS data for the third trip for 2009 of Vessel X. See caption for Figure 13.3 for details.

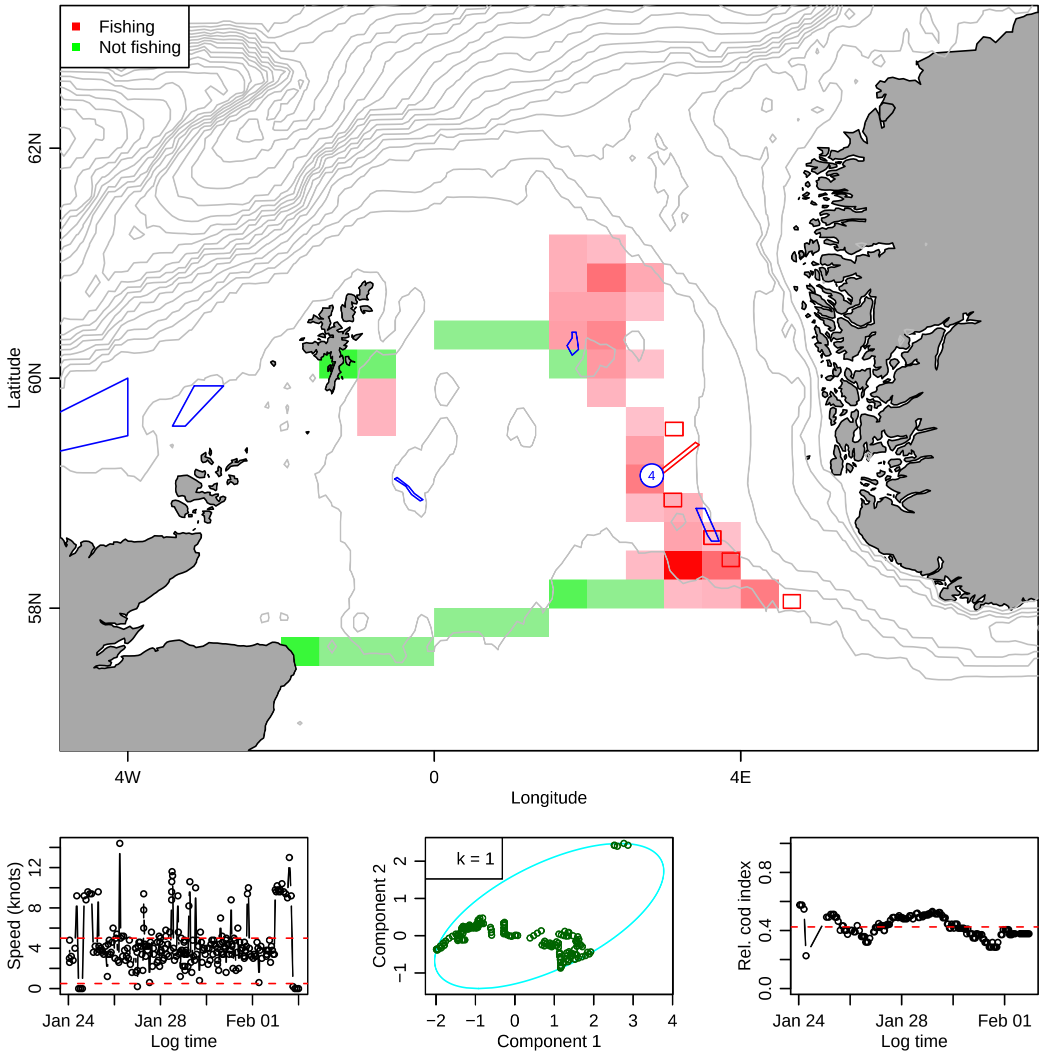


Figure 13.5: Summary of VMS data for the fourth trip for 2009 of Vessel X. See caption for Figure 13.3 for details.

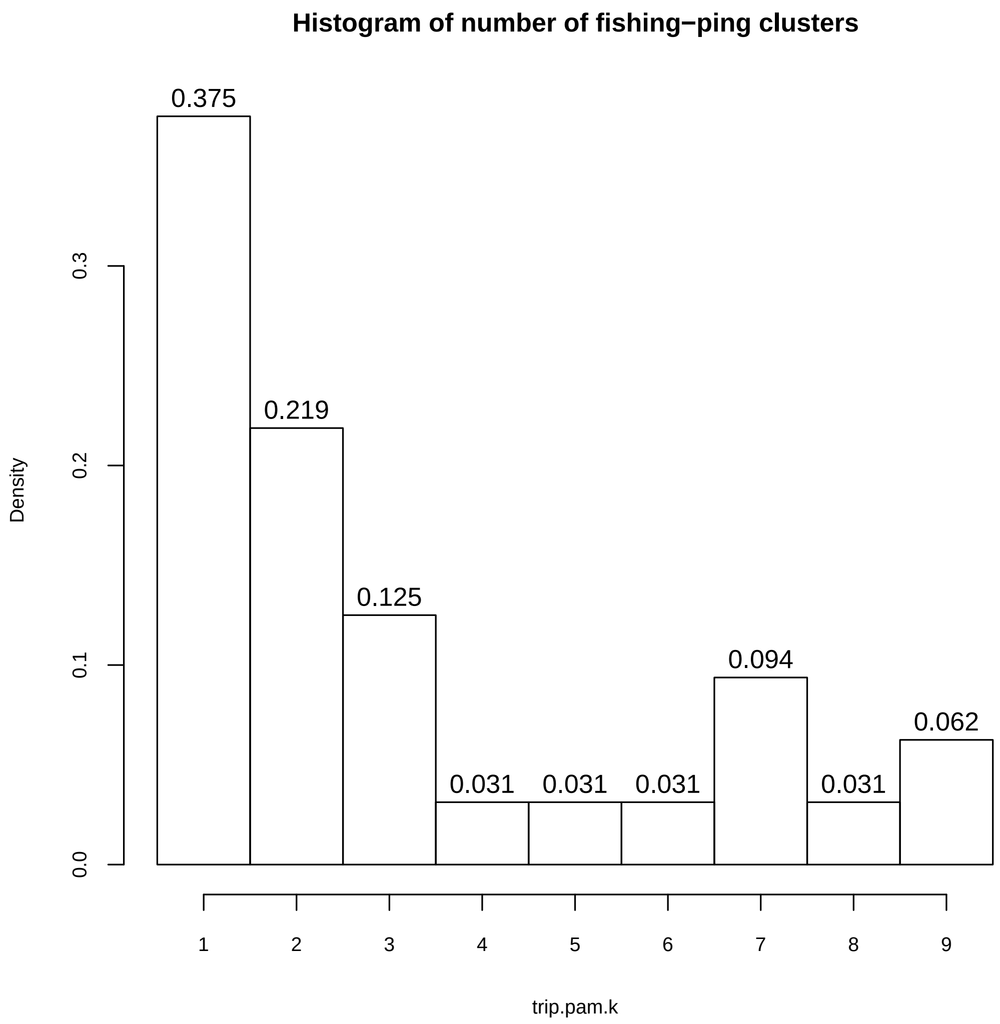


Figure 13.6: Histogram of the number of VMS fishing-ping clusters indicated per trip for Vessel X during 2009. The label “trip.pam.k” indicates the number of clusters per trip, while the proportion of the total number of trips for which the given number of clusters was indicated is shown at the top of each bar.

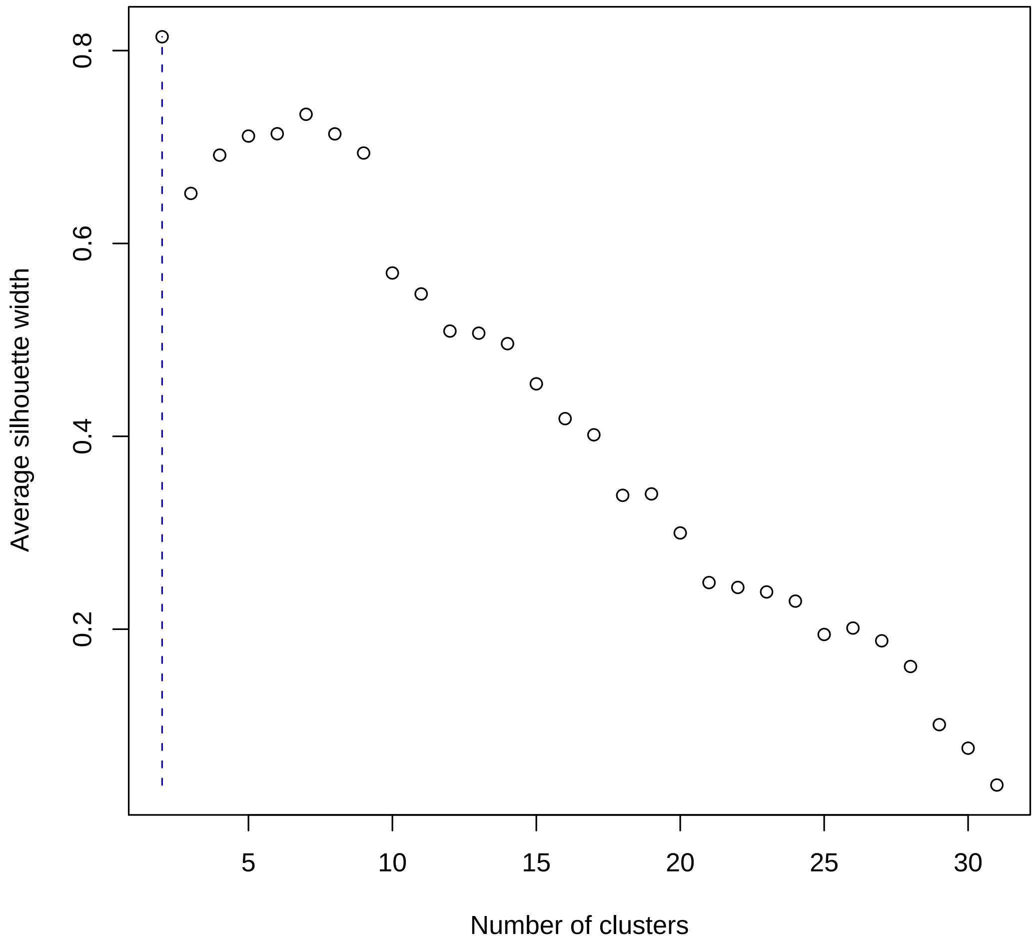


Figure 13.7: Cluster analysis of trip midpoints in 2009 for Vessel X: the average silhouette width s for all possible numbers of clusters. For each observation i, the silhouette width $s(i)$ is a measure of how well positioned in a cluster the observation is. Observations with $s(i) \simeq 1$ are very well clustered, $s(i) \simeq 0$ means that the observation lies between two clusters, and observations with $s(i) < 0$ are probably placed in the wrong cluster (Kaufman and Rousseeuw 2005). The vertical dashed line shows the number of clusters for which the average s is greatest, and therefore the suggested best clustering (in this case, the suggested number of clusters is 2).

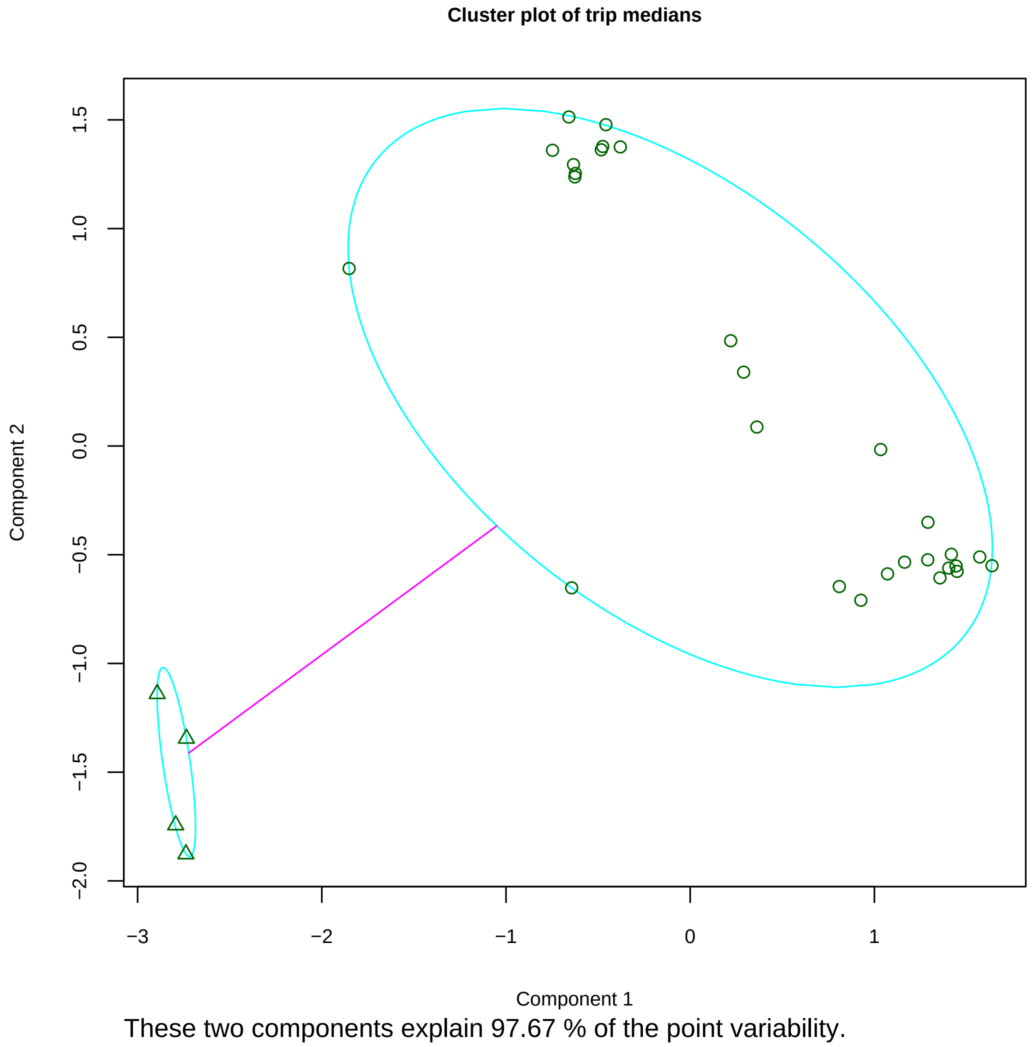


Figure 13.8: Cluster analysis of trip midpoints in 2009 for Vessel X: bivariate clustering plot. Ellipsoids indicate suggested clusters (Kaufman and Rousseeuw 2005).

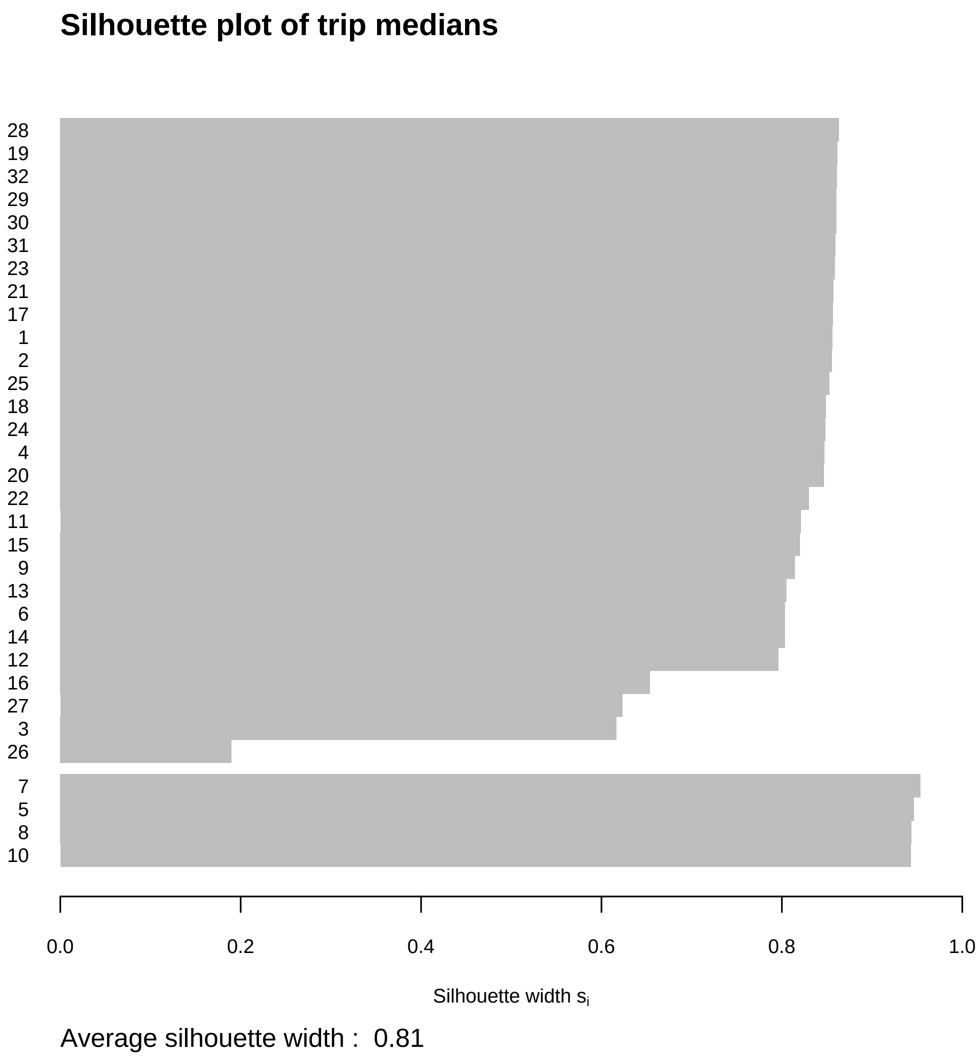


Figure 13.9: Cluster analysis of trip midpoints in 2009 for Vessel X: silhouette widths $s(i)$ for each observation, partitioned into suggested clusters. For each observation i, the silhouette width $s(i)$ is a measure of how well positioned in a cluster the observation is. Observations with $s(i) \simeq 1$ are very well clustered, $s(i) \simeq 0$ means that the observation lies between two clusters, and observations with $s(i) < 0$ are probably placed in the wrong cluster (Kaufman and Rousseeuw 2005). In this example, the Rockall cluster (lower) is very well-defined. The North Sea cluster (upper) is less well-defined: in particular, the grouping of observation 26 (a trip to the north-western shelf edge) is not very well-supported (see also Figure 13.10).

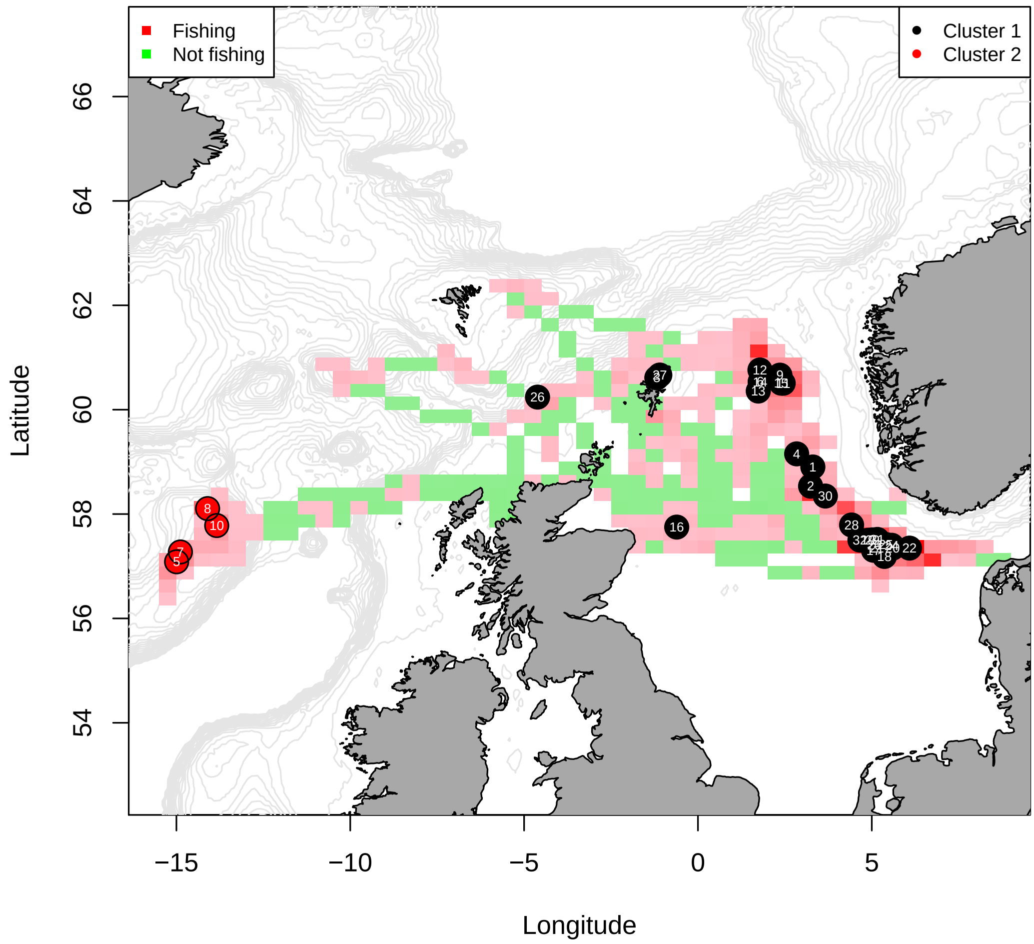


Figure 13.10: Aggregation summary of VMS pings for all trips for 2009 of Vessel X. Aggregation bins are $0.5^{\circ} \times 0.25^{\circ}$ rectangles, shaded by ping abundance (darker colours indicate more pings). Red shading shows fishing pings, green shading shows non-fishing pings. Note that only fishing pings are included in the shading for those bins with both fishing and non-fishing pings. Grey lines show bathymetry at 100-m intervals. The circled numbers show the locations of the geographic midpoints of the fishing pings for the trip, and are colour-coded according to cluster analysis (the colour legend is in the top right).

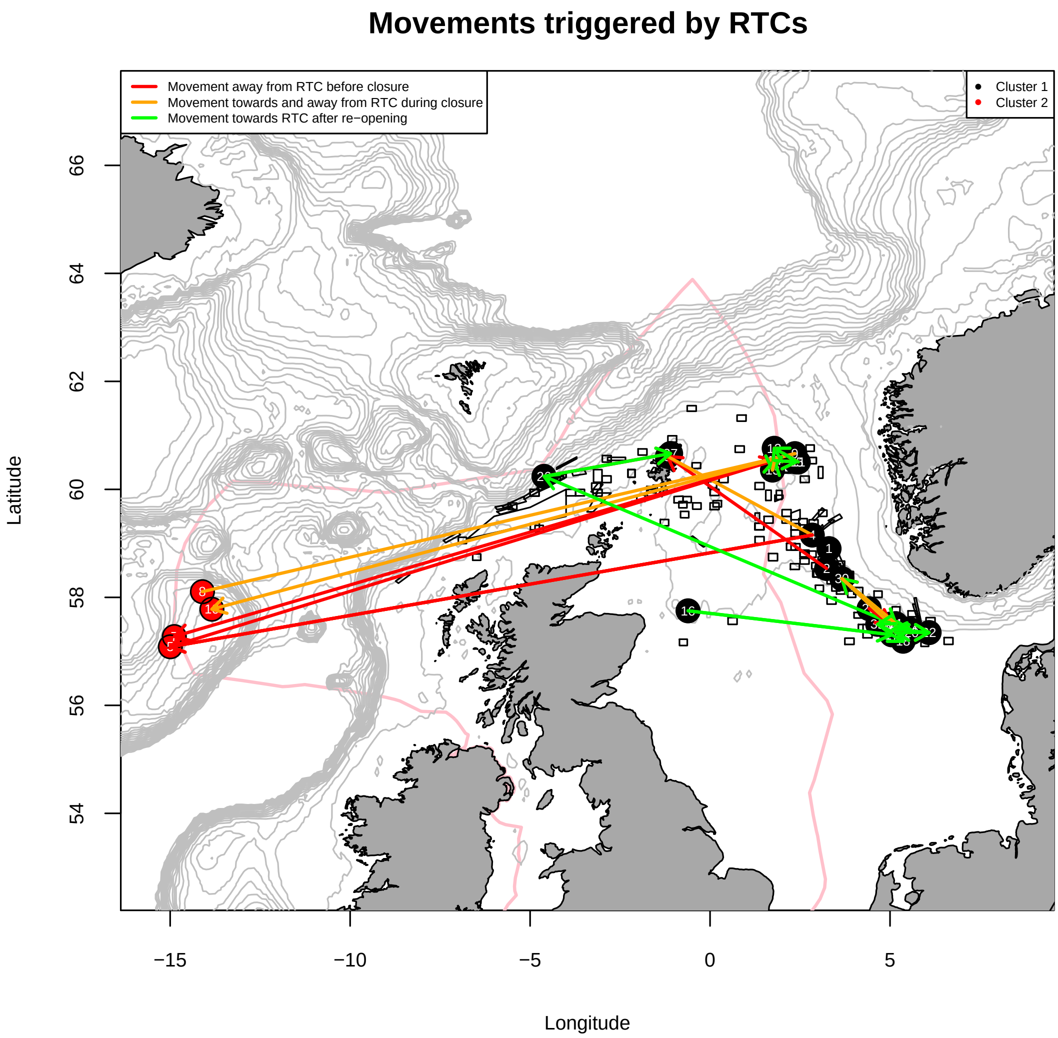


Figure 13.11: Summary of inter-trip movements preceded or followed by RTC involvement for Vessel X. RTCs are shown by black polygons. Grey lines show bathymetry at 100-m intervals, while the pink line shows the UK EEZ. The circled numbers show the locations of the geographic midpoints of the fishing pings for the trip, and are colour-coded according to cluster analysis (the colour legend is in the top right). Colour-coded arrows show the type of RTC involvement (the key is in the top-left).

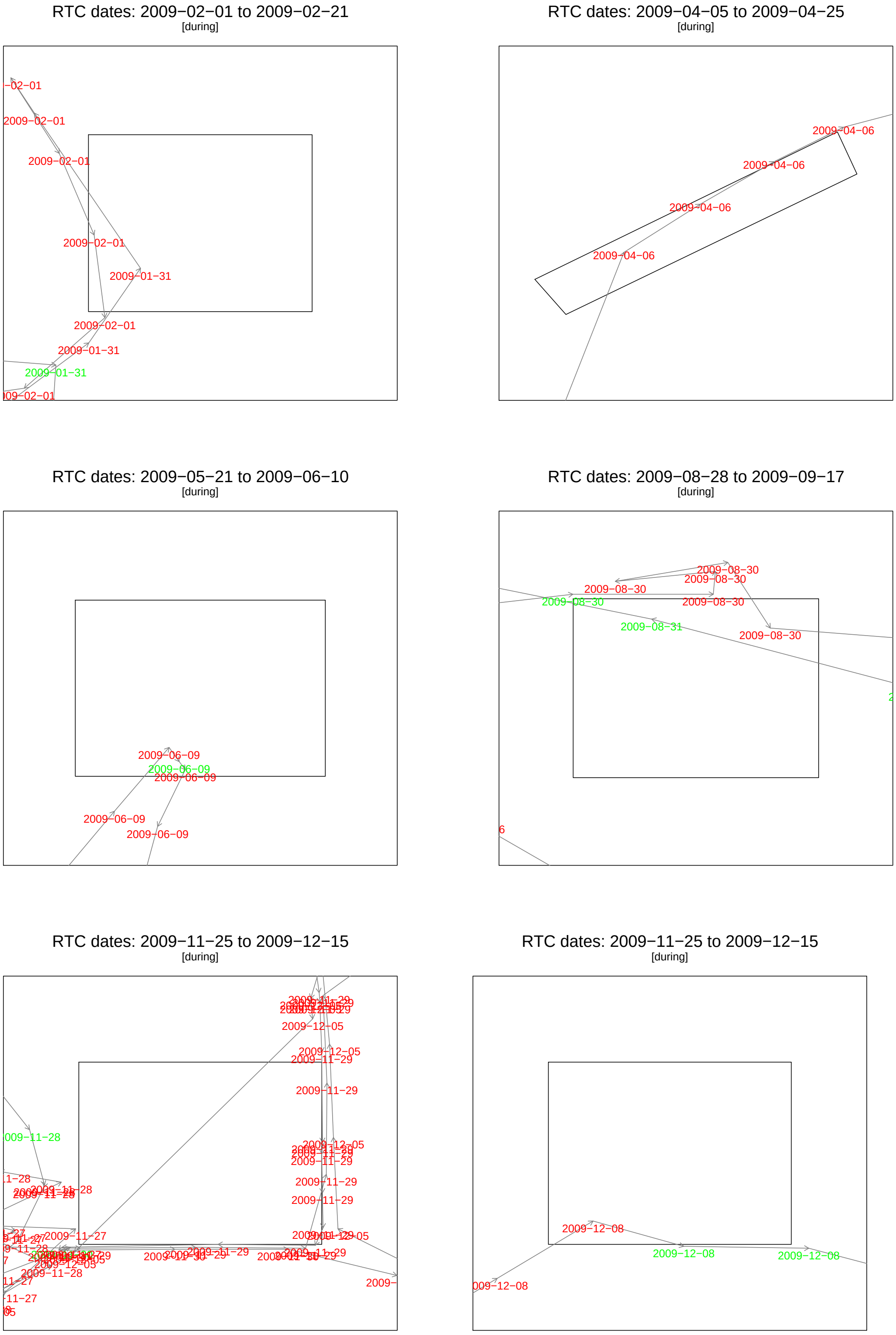


Figure 13.12: VMS pings for Vessel X in 2009 for those areas and times for which VMS data indicate Vessel X was fishing in RTCs. Lat-long information and RTC ID numbers have been removed to ensure anonymity: only ping dates remain. The RTC is shown by the central polygon. Fishing ping dates are shown in red, non-fishing ping dates in green. Grey arrows indicate direction of travel.

13.2.2 Results for all affected vessels in 2008-10

Full results are presented in Tables 13.3 to 13.5, and Figures 13.13 to 13.18. Note that these results refer to "affected" vessels. This is a convenient shorthand for vessels that fall into one of the three cases listed on page 145, but is not intended to imply that the fishing patterns of other vessels in the fleet are necessarily unaltered by the implementation of RTCs. Analyses of fishing patterns for the *whole* fleet are introduced in Chapter 14.

There were only 15 RTCs in 2008, and observance of them was not mandatory for the entire Scottish demersal whitefish fleet. Therefore, although the mean differences in RFII for cod were negative for case A for the full year, and for each of the quarters in which RTCs occurred in 2008, none of these differences are significantly different from zero by Student's t-tests (Table 13.3b, Figures 13.13 and 13.14). There are a range of mean differences for cases B and C, both positive and negative, but as none of these are significantly different from zero I cannot reach any conclusions for 2008.

In 2009, there were 144 RTCs, and full observance of the closures was mandatory for all Scottish whitefish demersal vessels. The higher number and greater extent of RTCs resulted in more observations of vessels in one or more of the three cases, and this is reflected in the greater significance of the mean RFII difference estimates for cod. Figure 13.15 shows that the average of the mean differences is negative over the whole year for cases A ("moving away") and B ("fishing during closure"), and positive for case C ("moving towards"), while Table 13.4b demonstrates that all these averages are *significantly* different from zero. Over the whole year, affected Scottish vessels were observed to move towards areas of lower cod importance (as measured by the RFII for cod) when moving away from newly-closed RTCs. This was also the case when fishing in RTCs during closures, although the example in Figure 13.12 suggests that many of these records may not truly indicate disregard of the closures. On the other hand, vessels were also observed to move back towards more important cod areas when RTCs were reopened. It should also be noted that the average of the mean RFII differences for cod for case A is very similar in absolute terms to the value for case C. Quarterly results for 2009 (Table 13.4b and Figure 13.16) show that the mean RFII differences for cod for case A were negative for all quarters in which there was a significant difference (the result for quarter 2 was slightly positive, but this is not statistically significant). All results for case B were negative, although only significantly so for quarters 2 and 4 (and I have suggested that indications of fishing "during" closures need to be interpreted carefully). Correspondingly, all significant results for case C were positive.

The number of RTCs in 2010 increased to 165, and the maximum possible extent of each increased to 225 square nautical miles. The likelihood of vessels encountering RTCs (in either of the three cases) was therefore substantially higher, and this is reflected in Table 13.5a which shows the increase in the number of vessels and trips directly affected by RTCs. The conclusions in terms of mean RFII differences for cod are very similar to 2009, however. Over the whole year, the mean difference for case A was significantly negative, implying that vessels moved to areas less important for cod when an RTC was imposed where they had been fishing (Table 13.5b and Figure 13.17). This is balanced, however, by a positive (and slightly greater) significant mean difference for case C, suggesting that vessels increased their potential impact on cod when moving back to newly-reopened RTCs. The comparison also holds for all quarters (Table 13.5b and Figure 13.18), although the negative difference for case A in quarter 1 is not significantly different to zero. Previous comments about the case B ("during") results hold here, although the results are included for completeness.

Regarding the distances moved by affected vessels, Tables 13.3c, 13.4c and 13.5c (as well as Figures 13.14, 13.16 and 13.18) indicate a fairly consistent pattern: distances moved for case A (moving away from RTCs) are greater than for case C (moving towards RTCs) for most of the year, before the pattern is reversed (in 2009 and 2010) in the third or fourth quarter. There is currently no explanation for this effect, although it could be explored using multi-annual VMS records for individual vessels (see Chapter 14).

To conclude: there is significant evidence for a decreased RFII for cod when vessels move away from newly-implemented RTCs (case A), but that the reduction in RFII for cod is at least matched by an equal and opposite *increase* in RFII for cod when vessels return to RTCs after reopening (case C), for the year as a whole and for all quarters. There are differences in the detail between the years, but this overall pattern appears to be maintained. These results suggest that RTCs encourage vessels to move away from cod-important areas when they are closed, but do not necessarily discourage renewed fishing on cod when they are reopened.

a)	all	q1	q2	q3	q4
Vessels in dataset	397	-	-	-	-
Vessels directly affected by RTCs	88	63	40	24	0
Trips directly affected by RTCs	257	135	77	45	0

b)	A: before		B: during		C: after	
all	-0.02	(p = 0.094)	0.014	(p = 0.337)	0.01	(p = 0.309)
q1	-0.003	(p = 0.746)	-0.017	(p = 0.384)	-0.007	(p = 0.562)
q2	-0.025	(p = 0.239)	0.044	(p = 0.066)	0.013	(p = 0.458)
q3	-0.051	(p = 0.186)	-0.006	(p = 0.272)	0.051	(p = 0.100)
q4	NA	(p = NA)	NA	(p = NA)	NA	(p = NA)

c)	A: before	B: during	C: after
all	166.0	128.2	99.9
q1	116.1	100.4	74.9
q2	198.3	160.3	120.6
q3	189.3	16.3	119.9
q4	NA	NA	NA

Table 13.3: Summary of RTC analysis for the affected vessels of the Scottish whitefish fleet in 2008. a) Numbers of vessels. b) Mean differences between mean RFII values for cod for pre- and post-closure trips of all affected Scottish demersal vessels, for the whole of 2008 and for each quarter thereof (Q1-Q4), and for each of the three cases (see text for details). "NA" indicates there were not enough relevant observations to calculate a mean. *p*-values of pairwise Student's *t*-tests carried out to determine whether values are statistically different from zero are given in parentheses: significant differences (at the 95% level) are shown in bold face. c) Means of the median distances (km) moved by all affected vessels between consecutive trips around closure periods for cod, for the whole of 2008 and for each quarter thereof (Q1-Q4), and for the three cases (see text for details). Cases and quarters for which relative RFII indices for cod between fishing grounds were significantly different at the 95% level (see Table 13.1) are marked by bold face.

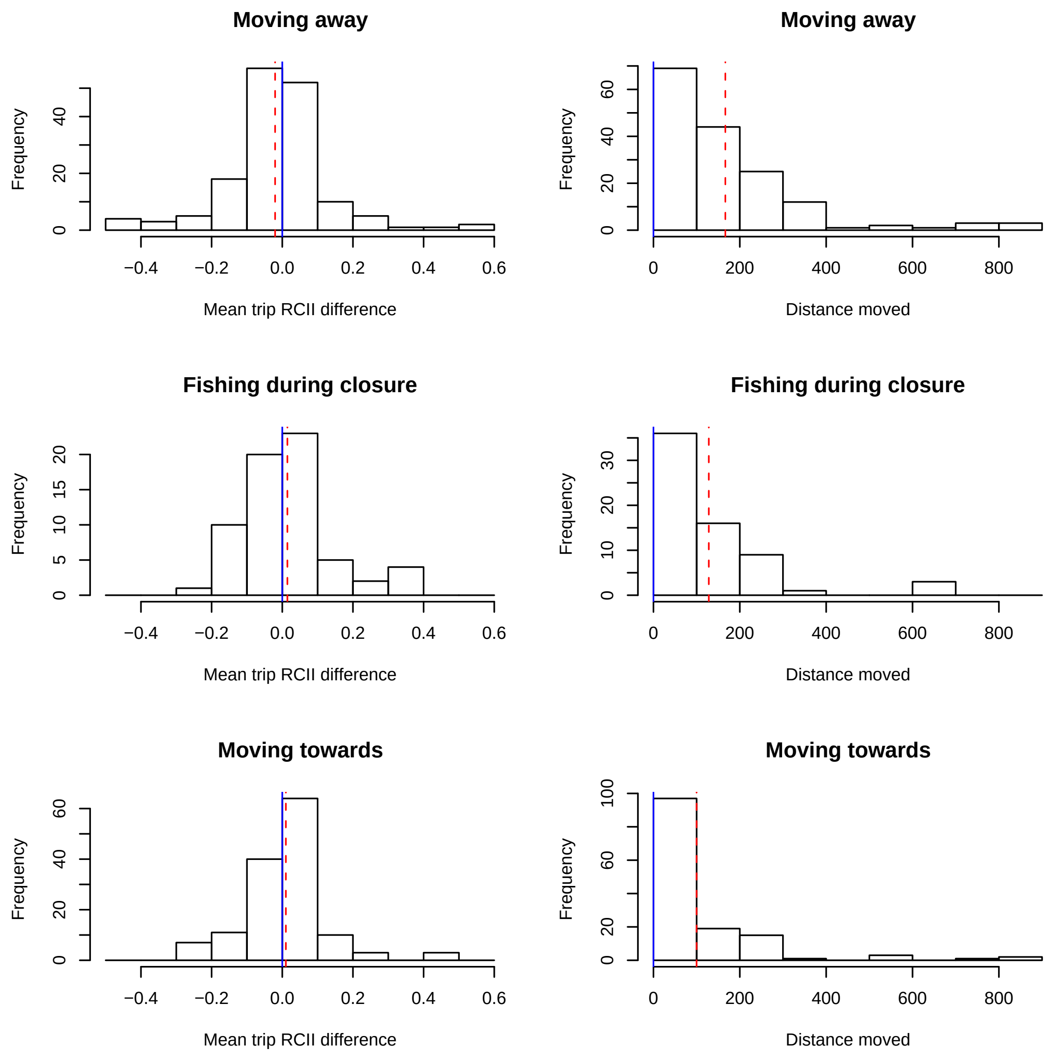


Figure 13.13: Histograms of results from VMS analyses for all affected Scottish vessels in 2008 (88 out of 397 in the VMS database). All three cases are included here, combined over all four quarters. Pre- and post-closure trips are compared in terms of (left panels) the difference in the mean RFII for cod for fishing pings, and (right panels) the distance moved between trips (km). The dashed vertical lines and the boxed numbers show means of each distribution.

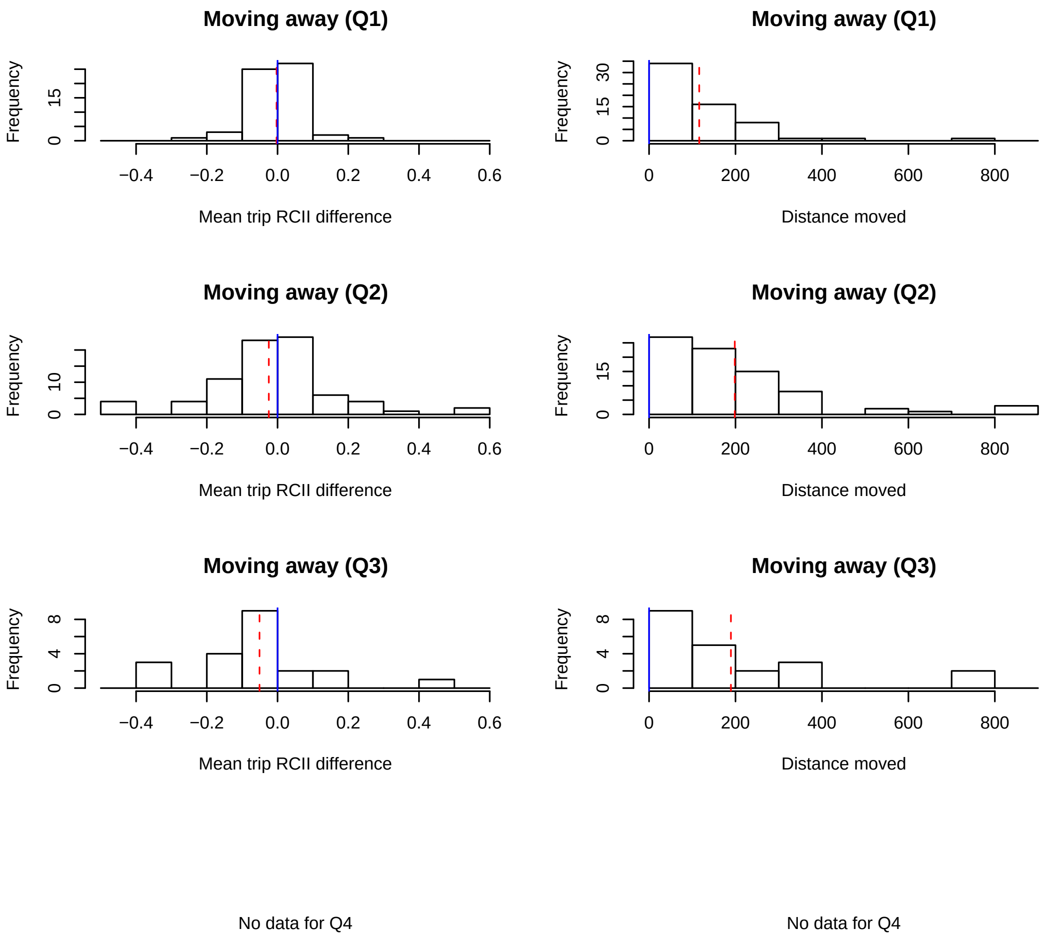


Figure 13.14: Histograms of results from VMS analyses for all affected Scottish vessels in 2008 (88 out of 397 in the VMS database). Only case A (moving away from an RTC after it is closed) is included here, and the four quarters of the year (Q1-Q4) are presented separately. Pre- and post-closure trips are compared in terms of (left panels) the difference in the mean RFII for cod for fishing pings, and (right panels) the distance moved between trips (km). The dashed vertical lines and the boxed numbers show means of each distribution.

a)	all	q1	q2	q3	q4
Vessels in dataset	403	-	-	-	-
Vessels directly affected by RTCs	153	97	102	93	87
Trips directly affected by RTCs	1007	218	290	272	227

b)	before		during		after	
all	**-0.031**	(p = 0.000)	**-0.039**	(p = 0.000)	**0.034**	(p = 0.000)
q1	**-0.051**	(p = 0.000)	**-0.058**	(p = 0.039)	-0.022	(p = 0.203)
q2	0.001	(p = 0.933)	-0.009	(p = 0.502)	**0.021**	(p = 0.007)
q3	**-0.036**	(p = 0.001)	**-0.077**	(p = 0.000)	**0.071**	(p = 0.000)
q4	**-0.039**	(p = 0.001)	-0.031	(p = 0.096)	**0.038**	(p = 0.012)

c)	before	during	after
all	**142.6**	**164.5**	**120.7**
q1	**155.2**	**154.5**	76.5
q2	141.2	206.1	**129.6**
q3	**140.5**	**151.4**	**118.1**
q4	**129.4**	114.1	**135.1**

Table 13.4: Summary of RTC analysis for the affected vessels of the Scottish whitefish fleet in 2009. a) Numbers of vessels. b) Mean differences between mean RFII values for cod for pre- and post-closure trips of all affected Scottish demersal vessels, for the whole of 2009 and for each quarter thereof (Q1-Q4), and for each of the three cases (see text for details). "NA" indicates there were not enough relevant observations to calculate a mean. *p*-values of pairwise Student's *t*-tests carried out to determine whether values are statistically different from zero are given in parentheses: significant differences (at the 95% level) are shown in bold face. c) Means of the median distances (km) moved by all affected vessels between consecutive trips around closure periods for cod, for the whole of 2009 and for each quarter thereof (Q1-Q4), and for the three cases (see text for details). Cases and quarters for which relative RFII indices for cod between fishing grounds were significantly different at the 95% level (see Table 13.1) are marked by bold face.

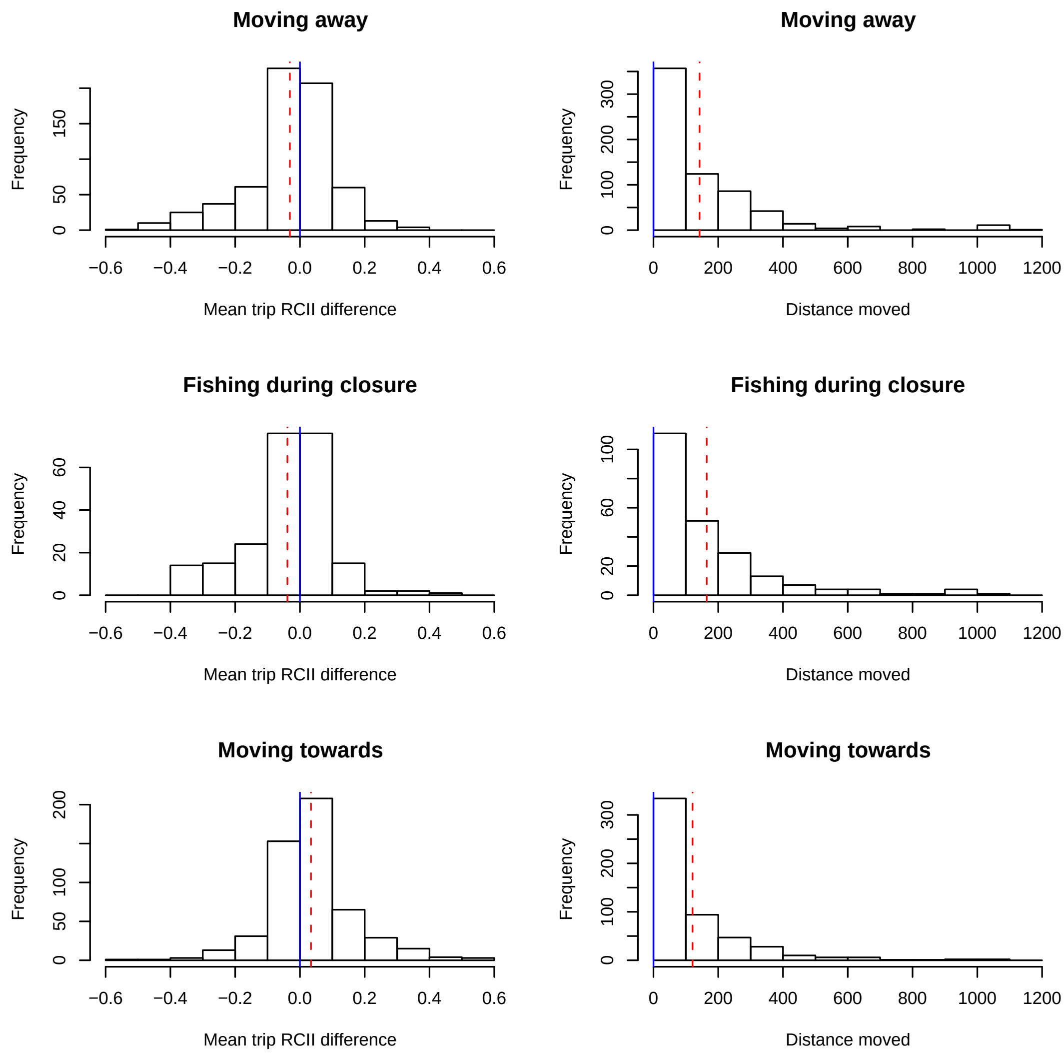


Figure 13.15: Histograms of results from VMS analyses for all affected Scottish vessels in 2009 (153 out of 403). All three cases are included here, combined over all four quarters. Pre- and post-closure trips are compared in terms of (left panels) the difference in the mean RFII for cod for fishing pings, and (right panels) the distance moved between trips (km). The dashed vertical lines and the boxed numbers show means of each distribution.

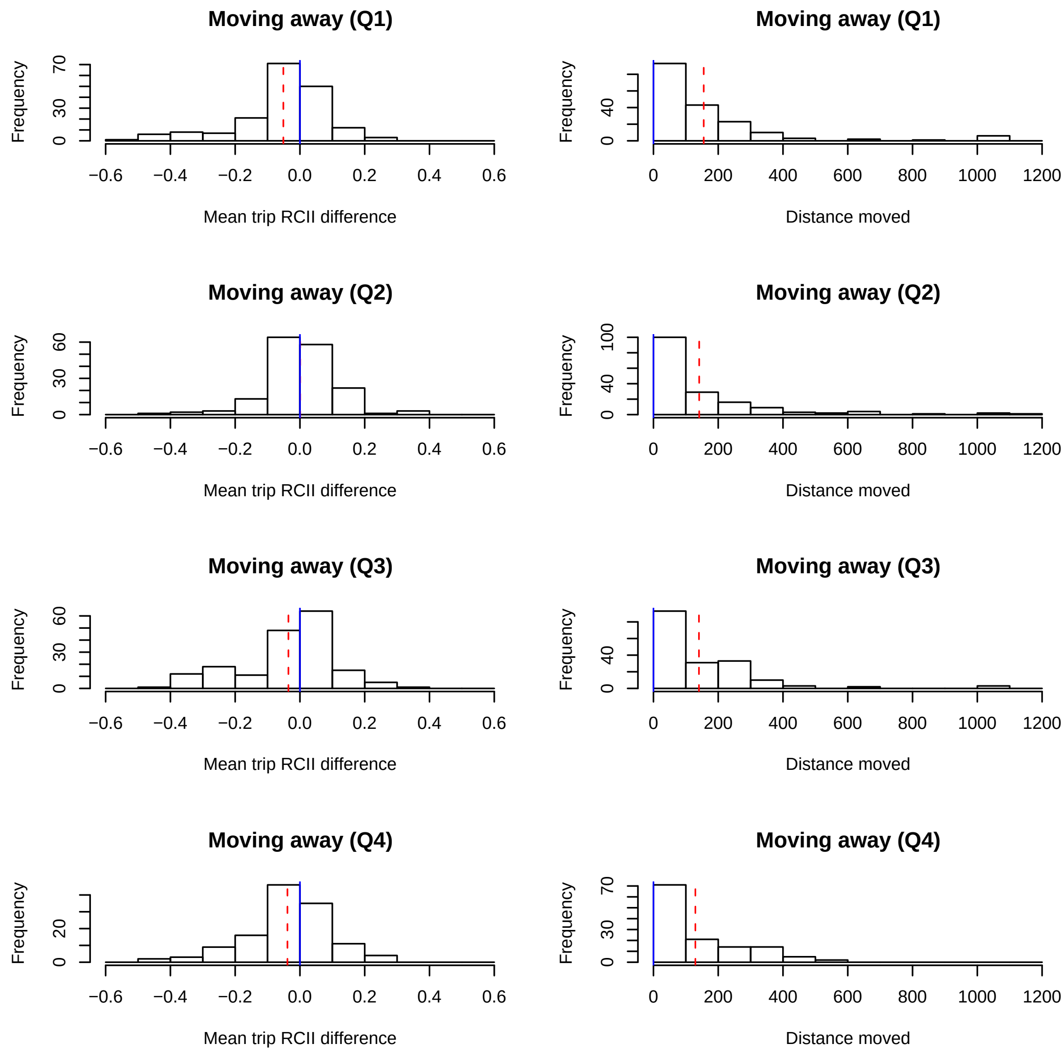


Figure 13.16: Histograms of results from VMS analyses for all affected Scottish vessels in 2009 (153 out of 403). Only case A (moving away from an RTC after it is closed) is included here, and the four quarters of the year (Q1-Q4) are presented separately. Pre- and post-closure trips are compared in terms of (left panels) the difference in the mean RFII for cod for fishing pings, and (right panels) the distance moved between trips (km). The dashed vertical lines and the boxed numbers show means of each distribution.

a)	all	q1	q2	q3	q4
Vessels in dataset	403	-	-	-	-
Vessels directly affected by RTCs	207	156	117	117	123
Trips directly affected by RTCs	1543	360	301	429	453

b)	before		during		after	
all	**-0.053**	(p = 0.000)	**-0.027**	(p = 0.002)	**0.057**	(p = 0.000)
q1	-0.014	(p = 0.136)	-0.027	(p = 0.074)	**0.026**	(p = 0.009)
q2	**-0.036**	(p = 0.002)	0.009	(p = 0.680)	**0.036**	(p = 0.000)
q3	**-0.072**	(p = 0.000)	**-0.047**	(p = 0.001)	**0.065**	(p = 0.000)
q4	**-0.070**	(p = 0.000)	-0.026	(p = 0.220)	**0.079**	(p = 0.000)

c)	before	during	after
all	**136.1**	**131.1**	**125.1**
q1	117.0	108.4	**90.9**
q2	**154.0**	145.4	**114.7**
q3	**143.3**	**132.4**	**152.2**
q4	**123.8**	136.8	**126.2**

Table 13.5: Summary of RTC analysis for the affected vessels of the Scottish whitefish fleet in 2010. a) Numbers of vessels. b) Mean differences between mean RFII values for cod for pre- and post-closure trips of all affected Scottish demersal vessels, for the whole of 2010 and for each quarter thereof (Q1-Q4), and for each of the three cases (see text for details). "NA" indicates there were not enough relevant observations to calculate a mean. *p*-values of pairwise Student's *t*-tests carried out to determine whether values are statistically different from zero are given in parentheses: significant differences (at the 95% level) are shown in bold face. c) Means of the median distances (km) moved by all affected vessels between consecutive trips around closure periods for cod, for the whole of 2010 and for each quarter thereof (Q1-Q4), and for the three cases (see text for details). Cases and quarters for which relative RFII indices for cod between fishing grounds were significantly different at the 95% level (see Table 13.1) are marked by bold face.

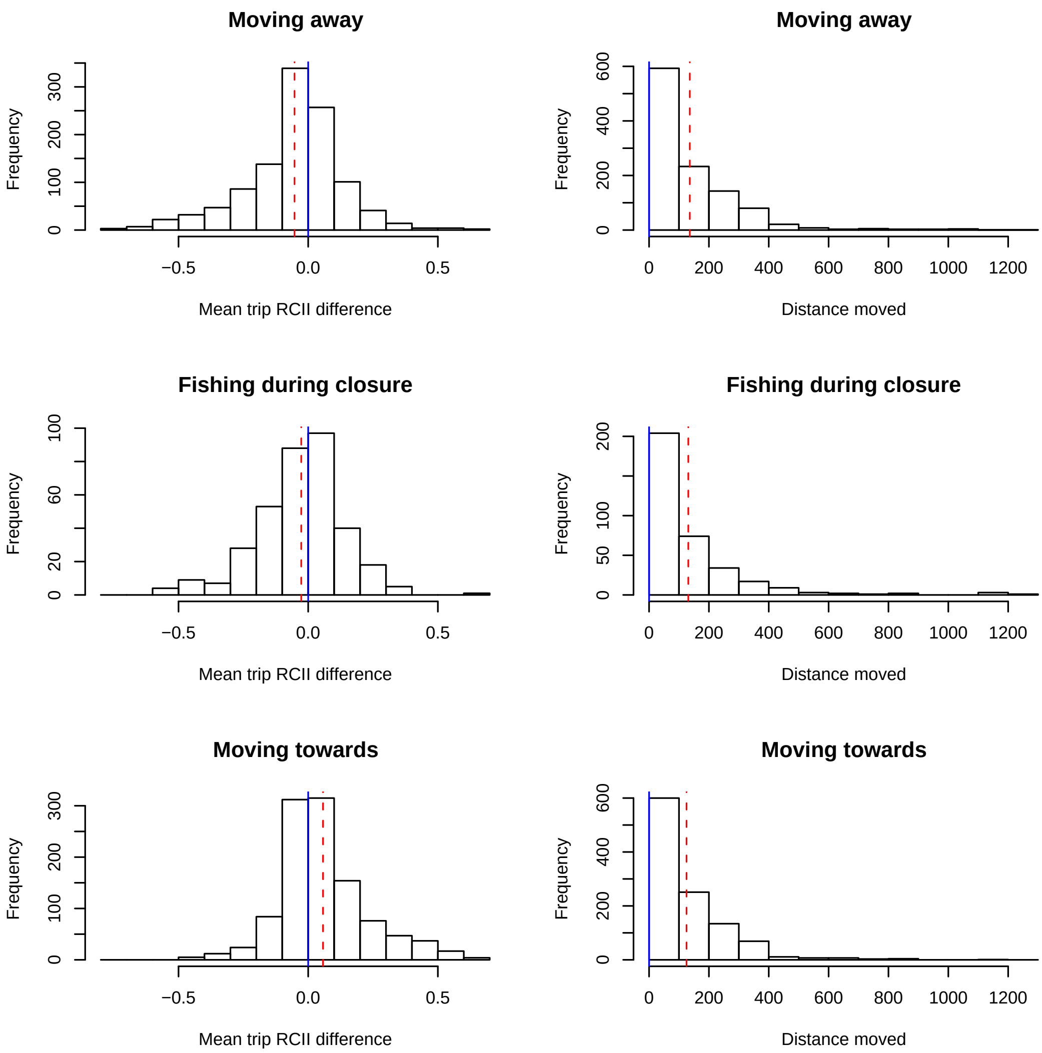


Figure 13.17: Histograms of results from VMS analyses for all affected Scottish vessels in 2010 (207 out of 403 in the VMS database). All three cases are included here, combined over all four quarters. Pre- and post-closure trips are compared in terms of (left panels) the difference in the mean RFII for cod for fishing pings, and (right panels) the distance moved between trips (km). The dashed vertical lines and the boxed numbers show means of each distribution.

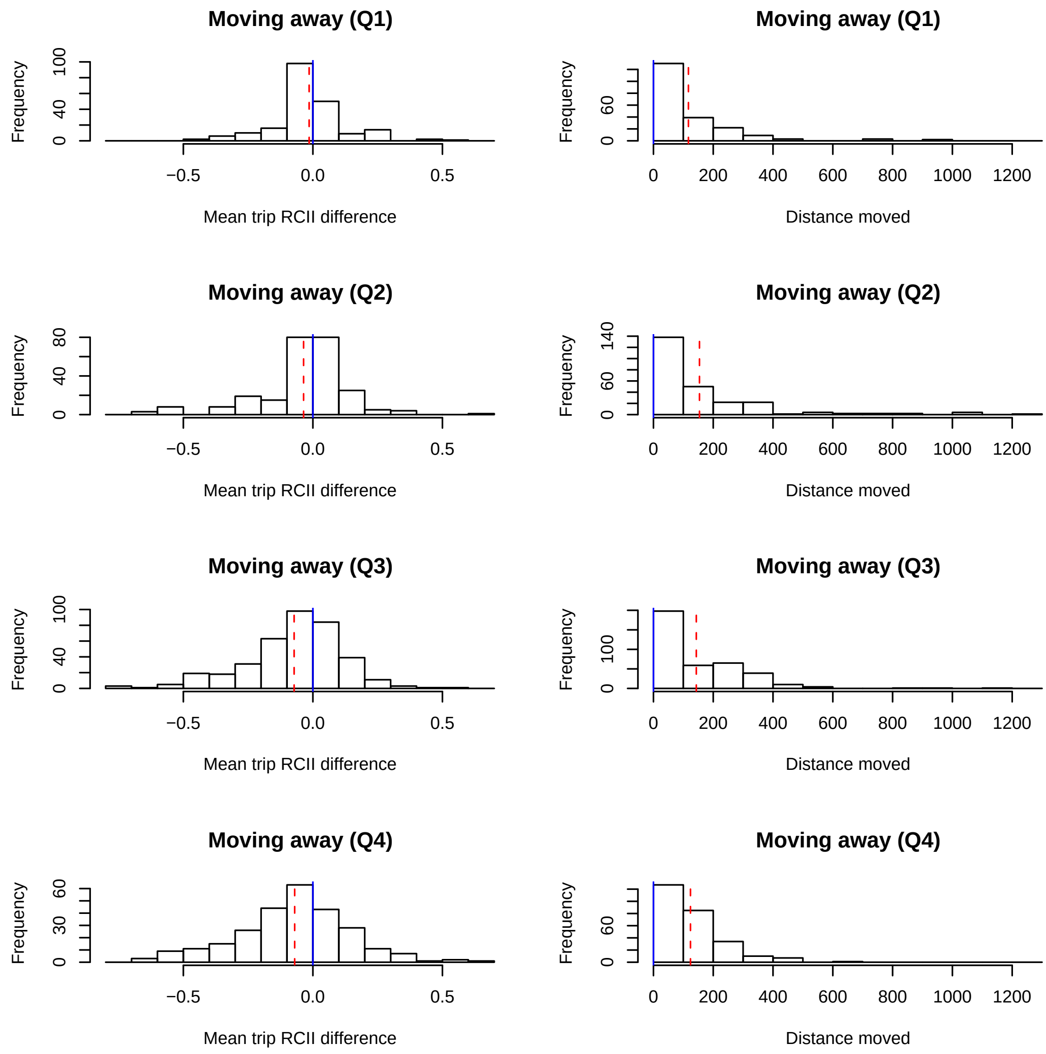


Figure 13.18: Histograms of results from VMS analyses for all affected Scottish vessels in 2010 (207 out of 403 in the VMS database). Only case A (moving away from an RTC after it is closed) is included here, and the four quarters of the year (Q1-Q4) are presented separately. Pre- and post-closure trips are compared in terms of (left panels) the difference in the mean RFII for cod for fishing pings, and (right panels) the distance moved between trips (km). The dashed vertical lines and the boxed numbers show means of each distribution.

14 Effects on individual skippers of closures

The analyses of responses to real-time closures described in Sections 11 to 13 above, and in Needle and Catarino (2011, reproduced in Chapter VI), provide useful information the dynamics of a subset of the Scottish fleet for part of the time, but they are necessarily incomplete. In order to attempt to explain the responses of vessels to closures in a tractable way, I restricted the analysis to vessels which were fishing in areas that were subsequently closed within 14 days, or which fished within a closed area while it was closed, or which moved back to a reopened area within 14 days of reopening. However, through such an approach I can only characterise a relatively small proportion of the trips of these vessels. I also can say nothing about the rest of the fleet: a vessel which avoided an area altogether because of a real-time closure was following exactly the fishing pattern that the regulation was intended to generate, but such a vessel is explicitly excluded from the analyses presented above. The analysis was therefore insufficient as the basis for the characterisation of vessel responses that is required for the spatio-temporal model outlined in Chapter IV.

An alternative approach is to consider in more detail all the available VMS data for a particular vessel. Suppose there are such data from a vessel (which I'll refer to here as Vessel X) for three years: 2008, when the RTC scheme was in its infancy and the closures were thought to have been too small and few in number to significantly affect fishing locations, and 2009-2010, when there were many more (and larger) closures and changes in fishing patterns were to be expected. The relevant questions are: firstly, whether I can determine discrete fishing areas used by Vessel X; secondly, whether the extent to which these areas are used by Vessel X has changed over time; and thirdly, whether I can determine if such changes are related to changes in the density of real-time closures in those fishing areas.

In this Section, I develop a methodology for addressing these questions, and apply it to the analysis of VMS data from the relevant vessels in the Scottish whitefish fleet (that is, those which were subject to RTC regulations during 2008-2010). As I am not considering socio-economic or other drivers of changes in fishing practices, I will still not be able to determine *why* such changes have taken place. However, I can provide a more detailed and inclusive characterisation of fleet movements than that given by Needle and Catarino (2011), and the correlation analysis comparing fishing locations with real-time closures (while not proving causality) will provide a useful basis for further study. I will illustrate the methods used with reference to two specific vessels, chosen only because they were the first two relevant vessels (in terms of fishing location and gear type) in the VMS dataset, and then draw conclusions from the application of the methods to the entire dataset of relevant vessels.

14.1 VMS DATA

The VMS data used for this analysis are derived from the same database used in Section 12, with the addition of derived database fields for year (2008-2010) and quarter (1-4). To enable analyses for a specific vessel, the full VMS dataset was restricted to records specific to that vessel using the unique RSS (Registry of Shipping and Seamen) code. For example, Figure 14.1 shows all VMS pings for the years 2008-2010 for Vessels 1 and 2 in the dataset. Plots of pings aggregated over a quarter (or a longer time period) do not contravene privacy or confidentiality legislation, as long as the vessel concerned is not named (see Section 12.2.2).

It would not be sufficient to reach conclusions on whole-fleet dynamics from the analysis of one or two vessels, however. For a whole-fleet analysis (as presented towards the end of Section 14.3), a dataset of all *relevant* vessels is required: in other words, those vessels which would be expected to be subject to real-time closure regulations, and for which a change in fishing locations following RTCs would be a possible outcome.

Vessel subsetting from the full available VMS dataset for 2008-2010 therefore was therefore carried out according to the following steps:-

1. A list was generated for each year, containing the ID numbers of all vessels for which VMS data was reported for that year. The resulting three lists were denoted $\mathbf{V}_{08}$, $\mathbf{V}_{09}$ and $\mathbf{V}_{10}$.

2. A new list was generated, including only those vessels which provided VMS pings in every year: that is, all v_i such that $(v_i \in \mathbf{V}_{08}) \wedge (v_i \in \mathbf{V}_{09}) \wedge (v_i \in \mathbf{V}_{10})$.

3. The vessel list was further refined according to three criteria:-

VMS pings A plot of all VMS pings for 2008-2010 for each vessel was examined. Vessels were removed if their ping distribution was characteristic of a pelagic trawler (few pings, scattered along the shelf edge), an inshore *Nephrops* or scallops vessel (pings located close to the shore in discrete areas), or if all pings were too far south or north for the vessel concerned to be affected by Scottish RTCs.

Species landings compositions Those vessels which landed only scallop, crab (swimming or edible), lobster, blue whiting, mackerel or herring were also removed from the dataset. Vessels landing predominantly monkfish, megrim or *Nephrops* were not removed by this criterion, as they would still have been subject to RTC legislation and could well have fished in RTC areas.

Gear Consider the gear types listed in Table 12.1. Vessels or fishermen using certain gears would not be affected by RTCs, and so their movements following the introduction of RTCs cannot be considered to be indicative of a consequential response. However, it is more difficult definitively to identify relevant vessels through gear codes alone, as (for example) a demersal trawler fishing for gadoids and a pelagic trawler targetting mackerel could both use bottom otter trawls to fish successfully. To illustrate this, VMS data for the vessels considered in Figure 14.1 (Vessels 1 and 2) all showed the use of either bottom otter trawls (OTB) or otter twin trawls (OTT). Another vessel, which was removed from the analysis, used both bottom otter trawls (OTB) and midwater otter trawls (OTM) to fish for mackerel, and so in this case a simple inclusive gear-code criterion would not have been sufficient on its own. However, some gear codes clearly mark a vessel as one which would not usually be subject to RTC regulations: examples include OTM (midwater otter trawls, only used for pelagic fishing), DRB (boat dredge, for scallops), and FPO (covered pots or creels, used for crab fishing). Any vessel which fished using these gears, even if only for part of the study period, was removed from the analysis. The gear codes included in the final dataset are listed in Table 14.1.

The second of these steps (limiting the dataset to vessels with VMS data for every quarter in every year) reduced the size of the dataset from 425 vessels to 345. The first of the three criteria in step 3 (VMS pings) retained 204 (59%) of these, the second (species landings compositions) 278 (81%), and the third (gear codes) 249 (72%). If a vessel needs to satisfy all three criteria to be retained, the resultant dataset includes 188 vessels. This represents just 54% of the vessels with VMS data for every year, but is still a substantial sample of the Scottish whitefish and *Nephrops* fleets.

Note that the three criteria in step 3 agreed on whether to include or remove a vessel for 243 cases (70%). The disagreements arose mostly because:-

- Vessels were using appropriate gear and landings appropriate species, but were fishing too far south or west for RTCs to have any effect; or
- Vessels were fishing in RTC-prone areas, but were using creels to target crab or *Nephrops*.

Restricting the vessels considered in this way would also have been relevant for the analyses presented in Section 13. At the time of writing of Needle and Catarino (2011) this was not done due to a lack of extant information on gear types. It is possible that the conclusions of Section 13 could be biased due to the inclusion of non-relevant vessels, and this could to be addressed in future work. However, all the vessels included in Needle and Catarino (2011) had been fishing in or near the areas of RTCs during 2008-2010, which would not be characteristic for the vessels removed from the current analysis, so the likelihood of an incorrect conclusion in Section 13 is slim.

Code	Description
GN	Gill nets (not specified)
GNS	Set gillnets (anchored)
LLS	Set longlines
OTB	B trawls otter (side/stern not specified)
OTT	Twin trawls Otter twin multi trawls
PS	Purse seine
PTB	B trawls pair trawls (two vessels)
PTM	Mid trawls pair trawls (two vessels)
SSC	Boat/vessel seines-Scottish seines
TBB	B trawls Beam trawls

Table 14.1: Scottish fishing gear and method codes used in VMS data, and in Marine Scotland's Fisheries Information Network (FIN). This list is derived from Table 12.1, but retains only those gear types which would be expected to be affected by RTC legislation.

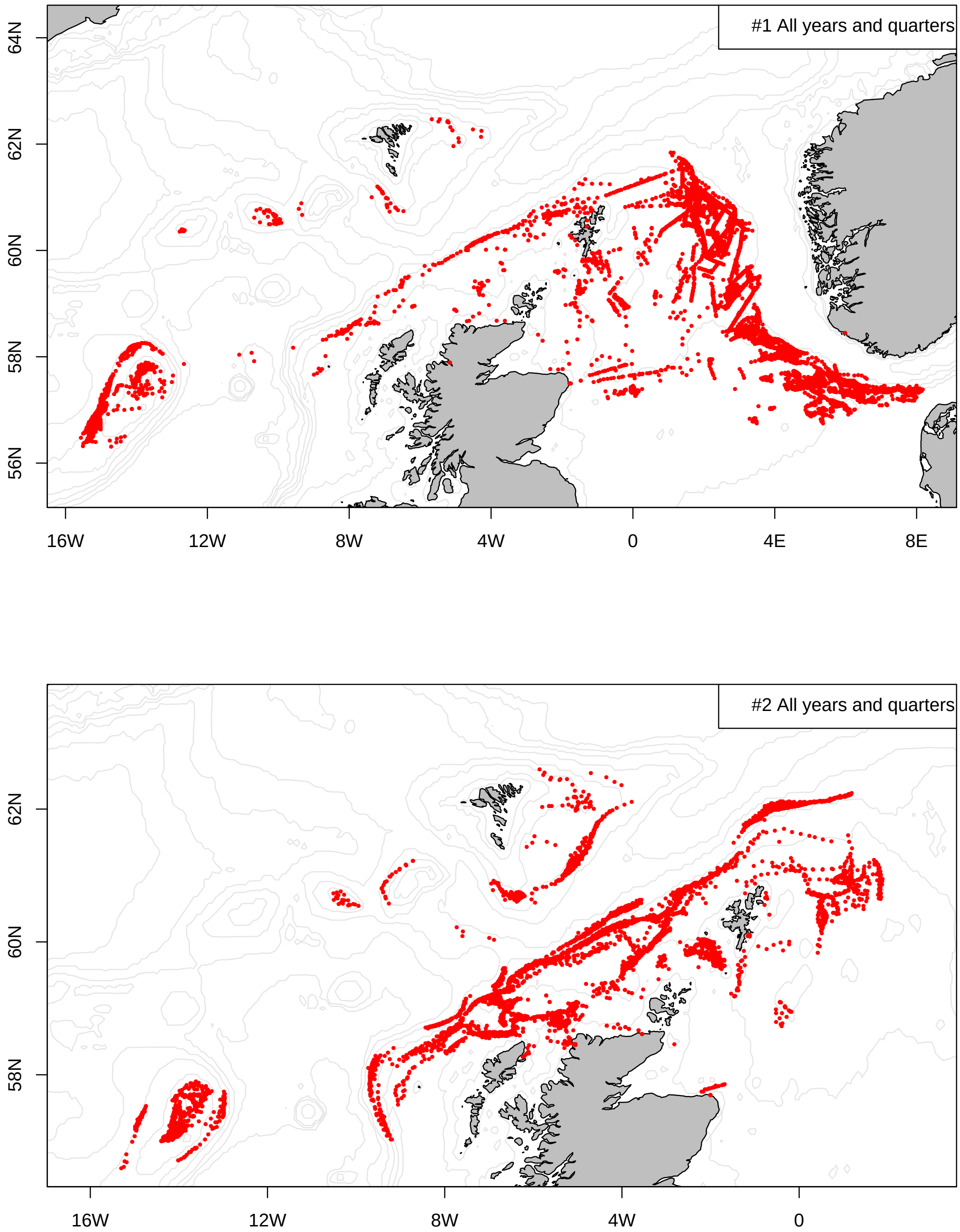


Figure 14.1: All VMS pings (red dots) transmitted by two Scottish fishing vessels during 2008-2010. Grey lines show bathymetry at 100-m intervals.

14.2 Cluster analysis of VMS data

In order to determine whether a vessel changes the location of fishing grounds from year to year, I need first to ascertain where those fishing grounds are. These will not be consistent across the fleet. Each vessel (by which I mean each skipper) will have a list of areas that they favour and in which they have fished successfully in the past, but the locations of these areas will depend on the experience of the skipper, the target species, the type of vessel being used, the distance to port, and a wide range of other factors (Hilborn and Ledbetter 1985, Thorlindsson 1994, Russel and Alexander 1996, Colding et al. 2000). A method is therefore needed for isolating discrete fishing areas, given detailed information from VMS pings on where the vessel concerned has been operating.

Categorising spatial information in this way leads quickly to considerations of cluster analysis (Kaufman and Rousseeuw 2005). This is a collection of techniques for quantitatively grouping spatial data on the basis of their locations (or other features), and has a long history in marine science (see, for example Nemec and Brinkhurst 1988, He et al. 1997, Spencer and Collie 1997). I have used cluster analysis previously in this thesis (Section 13): the following gives further relevant details.

The cluster analysis for this application was carried out in the R programming language (R Development Core Team 2011, version 2.8.1) using the `cluster` library (Maechler et al. 2005, version 1.11.11). This includes many different clustering methods, following Kaufman and Rousseeuw (2005), but the large number of VMS data points available from each fishing vessel in this study limits considerably the range of clustering methods available for this study. To see why this is, consider a set of n VMS pings $p_i = (x_i, y_i)$, where $i = 1, 2, \ldots, n$. Many cluster methods use as the basis for clustering a *dissimilarity matrix D*, which contains measures of the "distance" between each point and every other point, so that

$$D = \begin{bmatrix} d(p_1,p_1) & d(p_1,p_2) & d(p_1,p_3) & \ldots & d(p_1,p_n) \\ d(p_2,p_1) & d(p_2,p_2) & d(p_2,p_3) & \ldots & d(p_2,p_n) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d(p_n,p_1) & d(p_i,p_2) & d(p_i,p_3) & \ldots & d(p_i,p_n) \end{bmatrix} \tag{14.1}$$

which is a matrix with $n \times n$ elements. The widely-used distance metrics for spatial clustering include *Euclidean*, where the distances are the root of sum-of-squared differences

$$d\left(p_i, p_j\right) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \tag{14.2}$$

and *Manhattan*, where the distances are the sum of the absolute differences

$$d\left(p_i, p_j\right) = |x_2 - x_1| + |y_2 - y_1|. \tag{14.3}$$

In either case $d(p_i, p_j) = d(p_j, p_i)$ and $d(p_i, p_i) = 0$, so the matrix in Equation 14.1 can be simplified to the upper triangular form

$$D = \begin{bmatrix} d(p_1,p_2) & d(p_1,p_3) & \dots & d(p_1,p_n) \\ & d(p_2,p_3) & \dots & d(p_2,p_n) \\ & & \ddots & \vdots \\ & & & d(p_n,p_n) \end{bmatrix} \tag{14.4}$$

which is a matrix with $\frac{1}{2}n(n-1)$ elements. A typical VMS dataset for a specific vessel for the years 2008-2010 will contain around 5000 to 10000 records. For example, the dataset used to produce Figure 14.1 for Vessel 2 contains $n = 7220$ separate records. The dissimilarity matrix for the full dataset for that vessel would thus need to contain $\frac{1}{2}n(n-1) = 26060590$ elements, and would require 198.9 Mb of storage space. The default maximum for R (which is present to prevent problems with the other processes running on the computer) is around 84 Mb, so the full dissimilarity matrix for this vessel could not be stored in R. Even if the memory allocation was increased, the analysis would still run too slowly to be practical.

One possible approach to circumvent this limit would be to resample (without replacement) 10% to 20% of the available pings, and to run the cluster analysis on the basis of this reduced dataset. This would allow a wide range of clustering methods to be explored, but the pings that have been removed from the analysis cannot readily be assigned to clusters thereafter with this approach. Trial runs demonstrated that this approach led to unsatisfactory results.

The `cluster` library (Maechler et al. 2005) provides a solution to this problem via the CLARA method (Kaufman and Rousseeuw 2005). This is a subset of the PAM method (see below) which initially subsamples the ping dataset as described above (the size of the sampled sets can be set by the user). Once clustering has been carried out on the subset, following the PAM method, the remaining pings are assigned to clusters by computing distances to the cluster medoids (that is, the member of each cluster with the minimum average dissimilarity or distance to all the other members of the cluster). Medoids are conceptually similar to the mean or median of the cluster elements, except that a medoid is itself always a member of the cluster and is therefore more akin to the *mode* of a distribution.

The PAM cluster method ("partitioning around medoids": Kaufman and Rousseeuw 2005), on which CLARA is based, works as follows. Consider the dissimilarity matrix D (Equation 14.4), generated using either the Euclidean (Equation 14.2) or Manhattan (Equation 14.2) metrics from VMS data $p_i = (x_i, y_i)$ for $i = 1, 2, \ldots, n$. I set the number of clusters k that are required, although silhouette widths (see below) can be used subsequently to determine the optimum number of clusters. The method then finds the set of k *medoids* (also known in the clustering literature as *centrotypes* or simply *representative objects*) that minimise the average dissimilarity between each medoid and every member of its dependent cluster. A point becomes a member of a cluster if it is closer to that cluster's medoid than the medoid of any other cluster.

The algorithm proceeds in two steps. The first, known as the "build" step, seeks to designate an initial list of k medoids. The first such medoid is defined as the point for which the dissimilarity with all other points is minimised. The second step is to iteratively associate all points with appropriate medoids: details can be found in Kaufman and Rousseeuw (2005).

The standard fit diagnostic for the PAM method is the silhouette-width plot (Kaufman and Rousseeuw 2005), which is constructed as follows. For a given number of clusters k, every point i in the dataset has a silhouette width s_i which is given by

$$s_i = \frac{b_i - a_i}{\max\{a_i, b_i\}}. \tag{14.5}$$

Here a_i is defined as the average dissimilarity of i to all other points in the cluster to which it has been assigned (which I'll call A). If $d_{i,C}$ is the average dissimilarity of i to all points in clusters other than A (denoted here by C), then

$$b_i = \min_{C \neq A}\{d_{i,C}\}. \tag{14.6}$$

That is, the minimum of the dissimilarities (averaged over clusters) between point i and all points in clusters other than A. s_i can be thought of as measuring the average dissimilarity (or, for our purposes, distance) between point i and the nearest cluster to which i does not belong. Points for which s_i is large (close to 1.0) are very well-clustered, an s_i close to zero indicates that the point lies between two clusters, and a negative s_i suggests the point has been placed in the wrong cluster. Figure 14.2 illustrates silhouette widths for $k = 4$ and $k = 8$ when applied to the VMS data for Vessel 2 depicted in Figure 14.1. The average silhouette width for $k = 4$ for that vessel is 0.62, compared with 0.54 for $k = 8$, which suggests that the points are better characterised by four clusters than by eight (there are also six points when $k = 8$ for which $s_i < 0$, implying that they are probably in the wrong cluster).

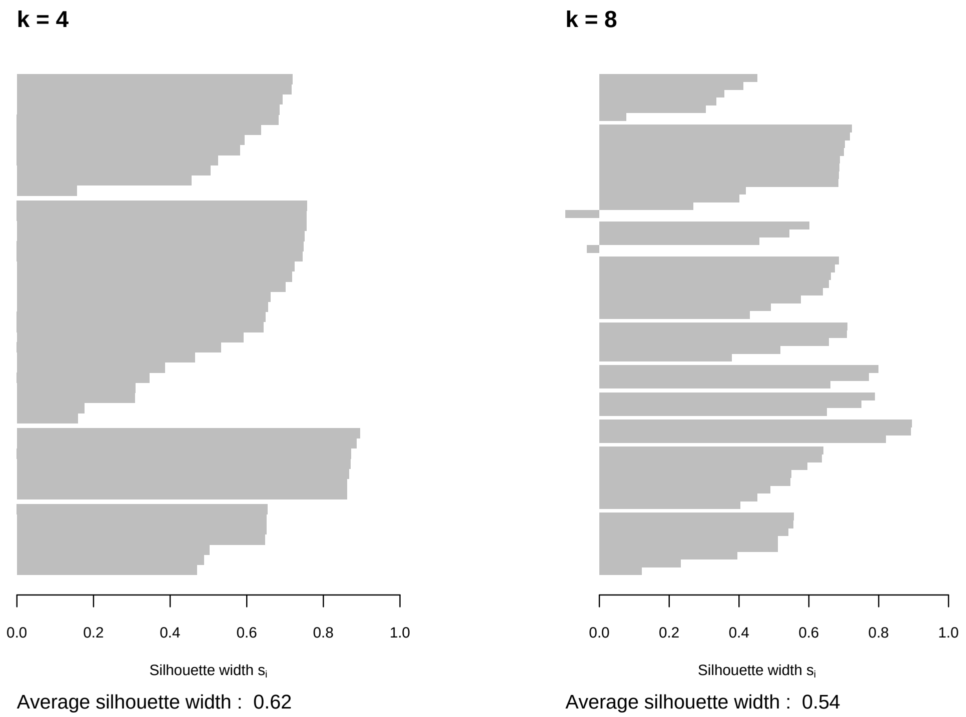


Figure 14.2: Silhouette widths s_i from a PAM cluster analysis applied to the VMS data for Vessel 2 presented in Figure 14.1, assuming $k = 4$ clusters (left) and $k = 8$ clusters (right). A value of s_i close to 1.0 indicates that point i is characterised well by its cluster.

The CLARA algorithm is an example of a clustering method that based on the minimisation of sums or averages of dissimilarities, and is therefore referred to as an L_1 method. The alternative L_2 family of methods are based on sums-of-squares of dissimilarities. In general, L_1 methods are more computationally intensive but have the advantage of being more robust, in the sense of being less susceptible to outliers (Kaufman and Rousseeuw 2005). Many clustering methods exist, however, and the choice between them can be difficult to justify. For the purposes of VMS analysis, CLARA clustering has a tendency to generate clusters that appear to have disparate outliers, or which subdivide locations that a visual inspection would suggest should remain undivided. An example is the clustering (with $k = 17$) in Figure 14.8 of the VMS data for Vessel 2 first presented in Figure 14.1. Here several of the clusters lie where I would expect: cluster 13 at Rockall, for example, or cluster 10 to the north-east of Shetland. However, for that vessel, the group of points south of the Færoes, which is visually quite coherent in Figure 14.1, has been divided between three clusters on the basis of medoid distance. Another example is the group of points off Fraserburgh, which appears in Figure 14.8 grouped with points off Kinlochbervie. In many of these cases it is the eye that is deceived. Plots of VMS pings overlap, and it is hard to determine visually the true density of points on which the clustering method is based. A linear group of points, such as that along the continental shelf edge (Figures 14.1 and 14.8), will also tend to be split up on apparently arbitrary lines.

While the clusters produced by the CLARA method may not always conform to what a visual inspection would predict, they do have a sound statistical basis and the appropriateness of different values of k can readily be determined using silhouette diagnostics. However, in one key aspect the CLARA method can perform poorly. The purpose for our cluster analysis is to determine (as far as possible) discrete fishing grounds for a particular vessel: that is, what the skipper of that vessel would consider to be fishing grounds. Using a strictly statistical basis, CLARA will often generate clusters which (while best-fitting in terms of dissimilarities) are much too large to be thought of as discrete fishing grounds. A typical split is between the North Sea and the West of Scotland, and this level of aggregation is far too coarse to mean anything when trying to understand skippers' fishing-area choices. For this reason, an additional stage in the process was added, as follows.

A CLARA analysis was run for all $k = 2, \ldots, 50$, and the average silhouette width $\bar{s}_k$ recorded each time. According to the standard CLARA methodology, the cluster number $k_{\max}$ which maximises $\bar{s}_k$ should be used to identify the best-fitting cluster. For Vessel 1, Figure 14.3 (upper plot) shows that $k_{\max} = 7$ (note that I do not consider $k < 5$, on the assumption that every fishing vessel will have at least five discrete fishing areas). However, this level of clustering seems too crude: Figure 14.4 (upper plot) shows a large cluster which includes both grounds east of Orkney and south-west of the Færoes, and it is difficult to conclude that a skipper would consider that those areas comprised a single contiguous fishing location.

Another way to highlight a useful clustering level is to determine whether there is a value k_{nnd} such that both $\bar{s}_{k_{\text{nnd}}-1}$ *and* $\bar{s}_{k_{\text{nnd}}+1}$ are much less than $\bar{s}_{k_{\text{nnd}}}$: in other words, a clustering level that improves $\bar{s}$ considerably when compared with immediately neighbouring clustering levels. This is an important measure for many of the analyses in this study, since values of $\bar{s}_k$ are often very similar for wide ranges of k and with k_{nnd} I can isolate those values of k that actually make a difference. I can determine this using *neighbour difference*, defined as

$$\delta_k = (\bar{s}_k - \bar{s}_{k-1}) - (\bar{s}_{k+1} - \bar{s}_k)\,. \tag{14.7}$$

Then k_{nnd} is that value of k which maximises δ_k. Values of δ_k for Vessel 1 are shown in Figure 14.3 (middle plot), from which $k_{\text{nnd}} = 47$.

The final step is to combine these estimates, as I want to use a value of k that produces $\bar{s}_k$ that is both high in absolute terms, and high in relation to its immediate k-neighbours. To achieve this, both $\bar{s}_k$ and δ_k are rescaled to lie between 0 and 1, using:

$$\bar{s}_k^* = \frac{\bar{s}_k - \min_k\{\bar{s}_k\}}{\max_k\{\bar{s}_k\} - \min_k\{\bar{s}_k\}}, \quad (14.8)$$

$$\delta_k^* = \frac{\delta_k - \min_k\{\delta_k\}}{\max_k\{\delta_k\} - \min_k\{\delta_k\}}. \quad (14.9)$$

For each k, I calculate the sum of these two rescaled quantities,

$$\rho_k = \bar{s}_k^* + \delta_k^*. \quad (14.10)$$

Then the required clustering level k_{sum} is given by the k which maximises ρ_k. For vessel 1, Figure 14.3 (lower plot) shows that $k_{\text{sum}} = 47$, although there is very little difference between ρ_7 and ρ_{47} (recall that $k_{\text{max}} = 7$).

Figure 14.4 compares the estimated clusters for $k = k_{\text{max}} = 7$ (upper plot) and $k = k_{\text{sum}} = 47$ (lower plot). While 47 discrete fishing areas is a large number, the scale at which skippers operate is quite fine and trips to location 10 miles apart can often be thought as going to different locations. This is particularly true for vessels targeting species such as *Nephrops* which are very patchily distributed (ICES 2011c). Hence the fine distinction between areas suggested by the k_{sum} clustering is not difficult to justify, and certainly appears more useful for this vessel than the competing k_{max} clustering. Full CLARA diagnostics for both of these clustering runs are given in Figures 14.5 and 14.6

For comparison, I show the results of the same methodology applied to the VMS pings from Vessel 2 (plotted for 2008-2010 in Figure 14.1, lower plot). In this case, Figure 14.7 indicates that both k_{max} and k_{nnd} should be equal to 17, and therefore that $k_{\text{sum}} = 17$ as well. In this case, using 17 clusters results in both the highest absolute value of $\bar{s}_k$, and the highest value relative to immediate k-neighbours (assuming k is not less than 5). I have already commented on the clusters in Figure 14.8, although confidence in the appropriateness of this value of k must be increased by the fact that two different measures of cluster quality suggest $k = 17$. Finally, the silhouette-width plot in Figure 14.9 confirms that a block of points are probably not in the correct cluster: these are the points off Fraserburgh that were discussed above.

In summary, I have developed a method for determining possible discrete fishing grounds for any given vessel, on the basis of VMS fishing points from 2008-2010. The method uses a development of the CLARA cluster algorithm of Kaufman and

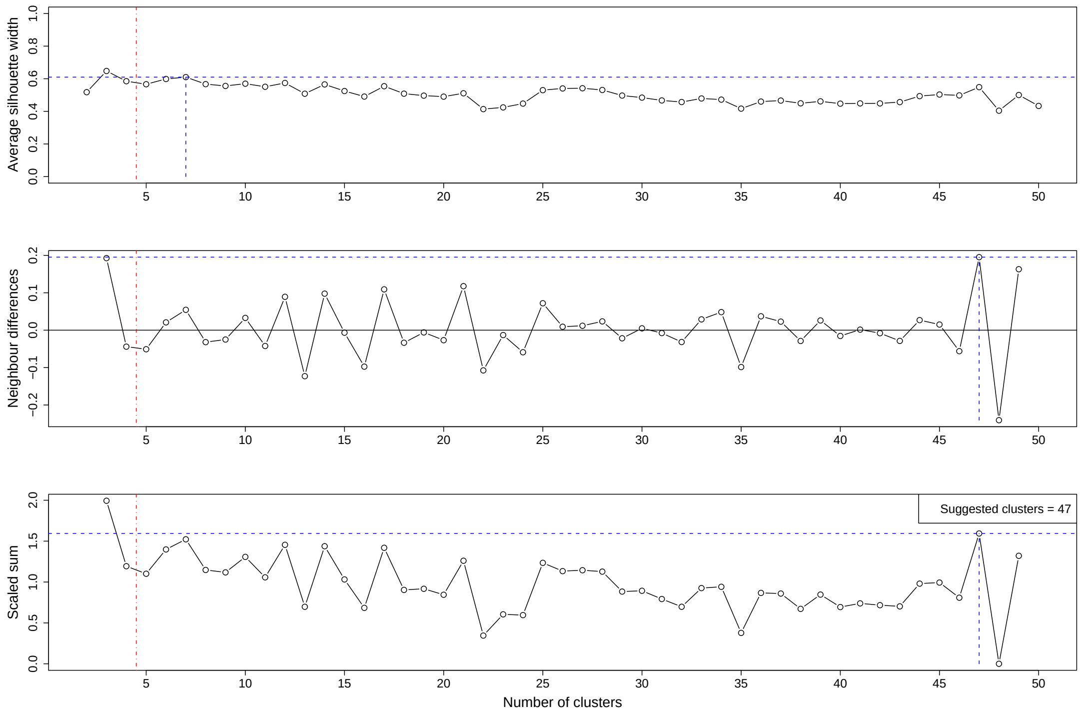
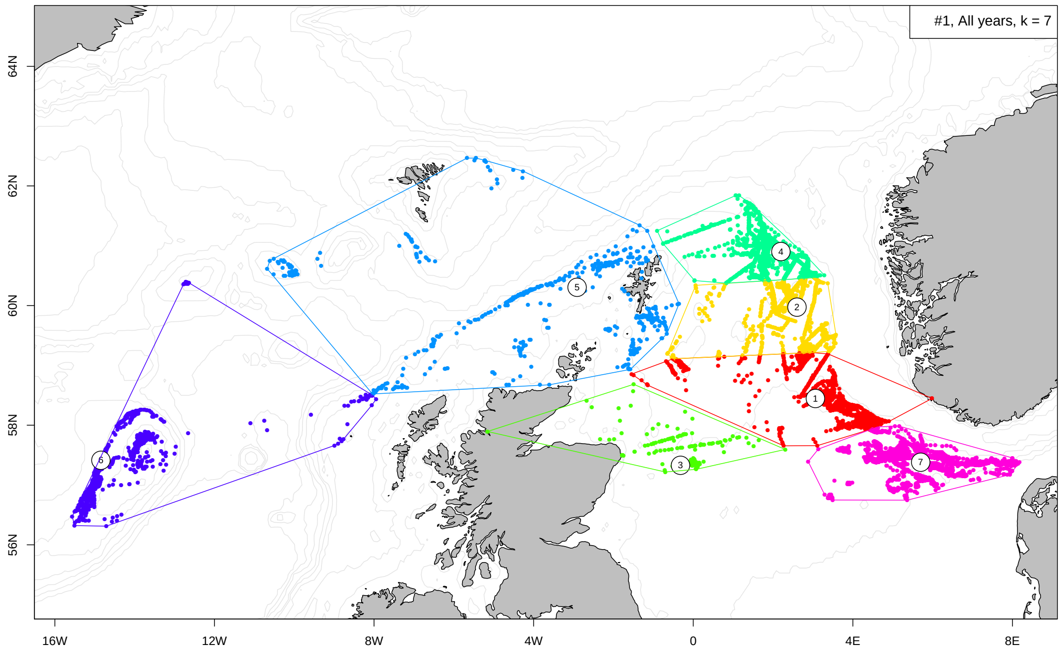


Figure 14.3: Determination of number of clusters k for Vessel 1. Upper plot: average silhouette width $\bar{s}_k$ for $k = 2, \ldots, 50$. Blue lines give $k_{\max}$ and $\max_k\{\bar{s}_k\}$. Middle plot: neighbour difference $\delta_k = (\bar{s}_k - \bar{s}_{k-1}) - (\bar{s}_{k+1} - \bar{s}_k)$. Blue lines give k_{nnd} and $\max_k\{\delta_k\}$. Lower plot: ρ_k, the scaled sum of $\bar{s}_k$ and δ_k. Blue lines give k_{sum} and $\max_k\{\rho_k\}$. In all plots the vertical red line shows the minimum k considered.

Rousseeuw (2005) to account for the relatively fine scale on which fishermen make decisions about fishing locations.



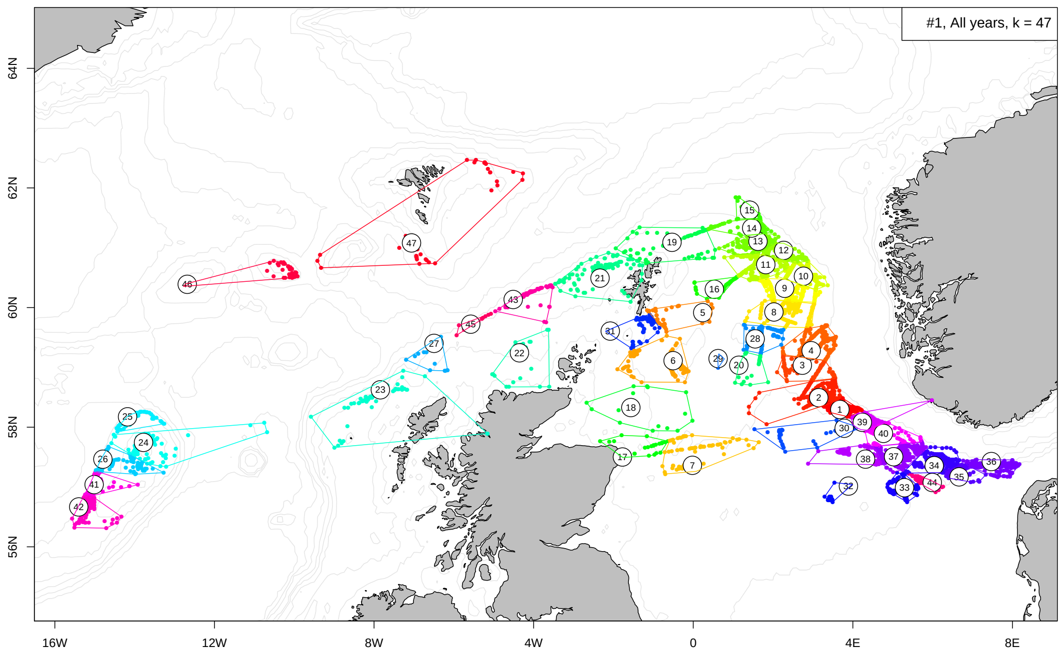


Figure 14.4: All VMS pings transmitted for Vessel 1 during 2008-2010, divided into $k = k_{\max} = 7$ (top) and $k = k_{\text{sum}} = 47$ (bottom) clusters using the CLARA method. All points within a cluster are plotted in the same colour, and the cluster is bound by a minimum convex polygon of the same colour. Circled numbers show the ID number of each cluster at the cluster medoid. Grey lines show bathymetry at 100-m intervals.

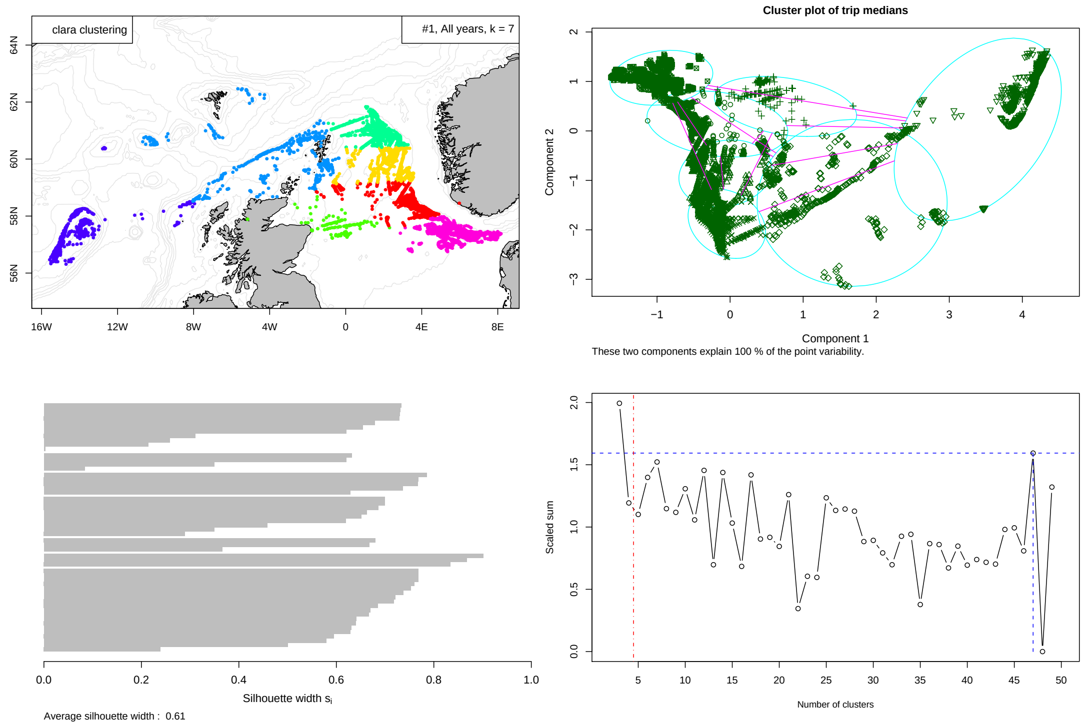


Figure 14.5: CLARA method diagnostics for cluster analysis of VMS data from Vessel 1, assuming $k = k_{\max} = 7$. Upper left: VMS pings for Vessel 1 (2008-10), coloured according to cluster membership. Upper right: the clusplot for the analysis (see Section 13.2 for a description). Symbols are the VMS points rescaled to lie on principal component axes. Each ellipse encloses all the rescaled observations from a given cluster, while lines are intended to indicate distance between clusters. Lower left: silhouette widths (see caption for Figure 14.2 for details). Lower right: scaled sums ρ_k (see caption for Figure 14.3 for details.)

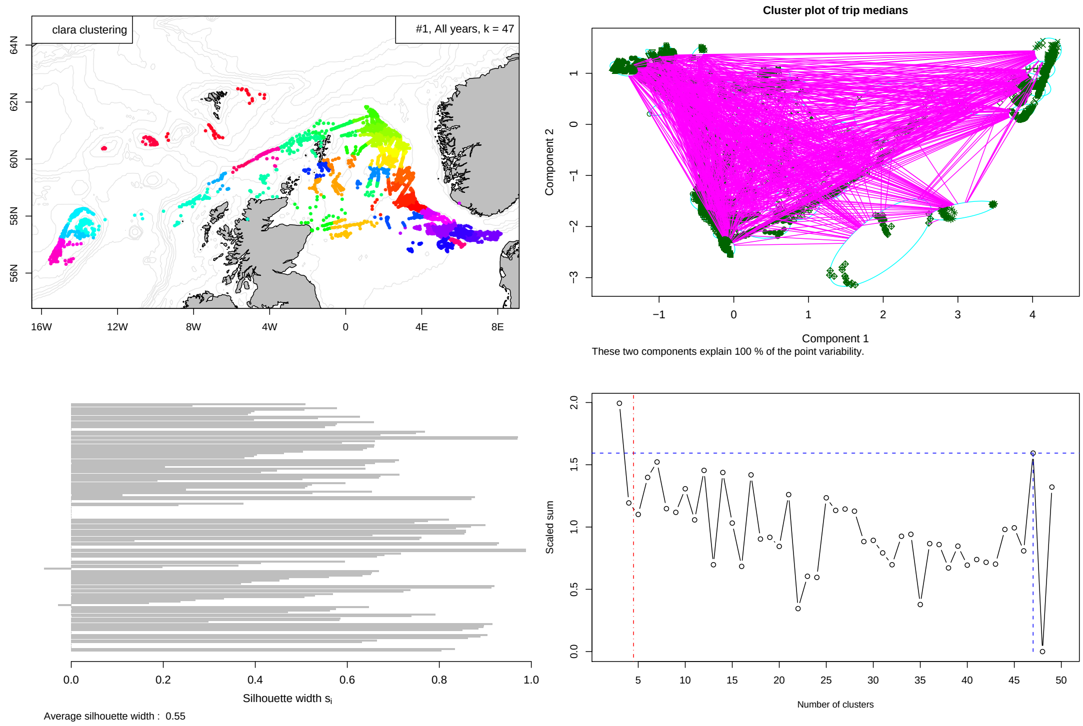


Figure 14.6: CLARA method diagnostics for cluster analysis of VMS data from Vessel 1, assuming $k = k_{\text{sum}} = 47$. Upper left: VMS pings for Vessel 1 (2008-10), coloured according to cluster membership. Upper right: the clusplot for the analysis (see Section 13.2 for a description). Symbols are the VMS points rescaled to lie on principal component axes. Each ellipse encloses all the rescaled observations from a given cluster, while lines are intended to indicate distance between clusters. Lower left: silhouette widths (see caption for Figure 14.2 for details). Lower right: scaled sums ρ_k (see caption for Figure 14.3 for details.)

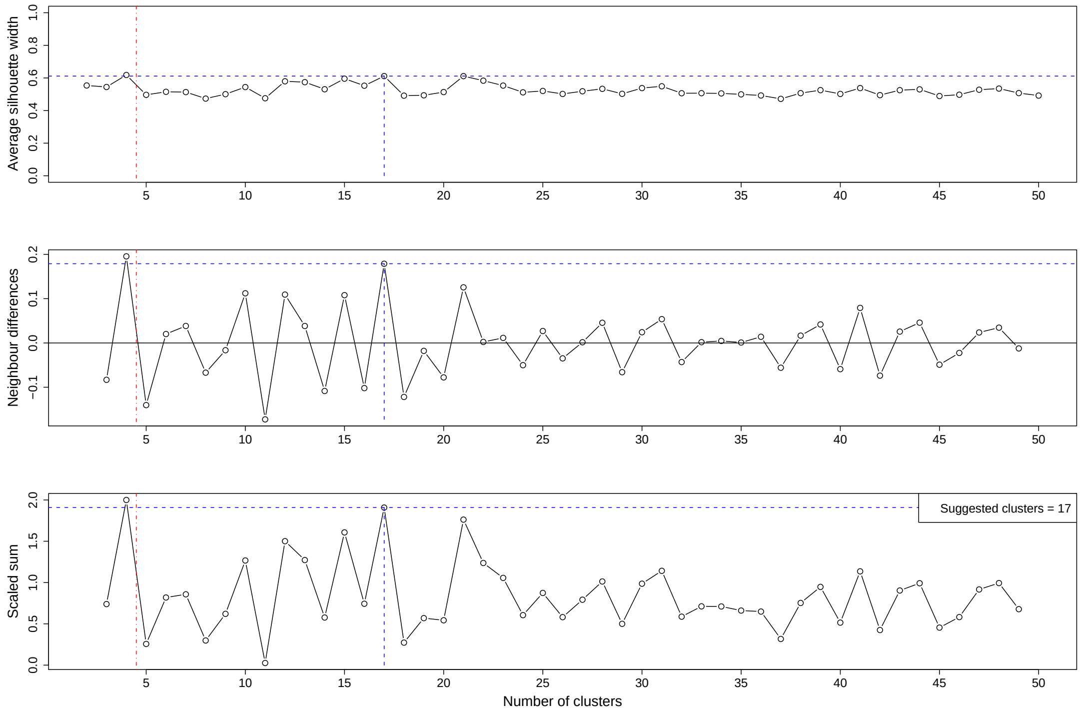


Figure 14.7: Determination of number of clusters k for Vessel 2. Upper plot: average silhouette width $\bar{s}_k$ for $k = 2, \ldots, 50$. Blue lines give k_{max} and $\max_k\{\bar{s}_k\}$. Middle plot: neighbour difference $\delta_k = (\bar{s}_k - \bar{s}_{k-1}) - (\bar{s}_{k+1} - \bar{s}_k)$. Blue lines give k_{nnd} and $\max_k\{\delta_k\}$. Lower plot: ρ_k, the scaled sum of $\bar{s}_k$ and δ_k. Blue lines give k_{sum} and $\max_k\{\rho_k\}$. In all plots the vertical red line shows the minimum k considered.

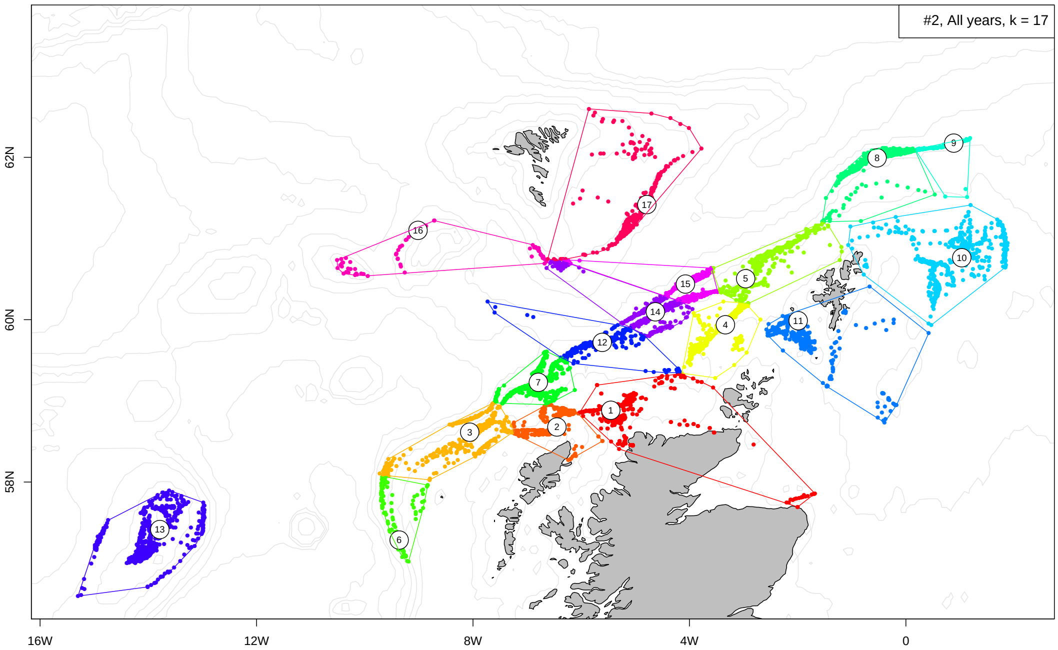


Figure 14.8: All VMS pings transmitted for Vessel 2 during 2008-2010, divided into $k = k_{\text{max}} = k_{\text{sum}} = 17$ clusters using the CLARA method. All points within a cluster are plotted in the same colour, and the cluster is bound by a minimum convex polygon of the same colour. Circled numbers show the ID number of each cluster at the cluster medoid. Grey lines show bathymetry at 100-m intervals.

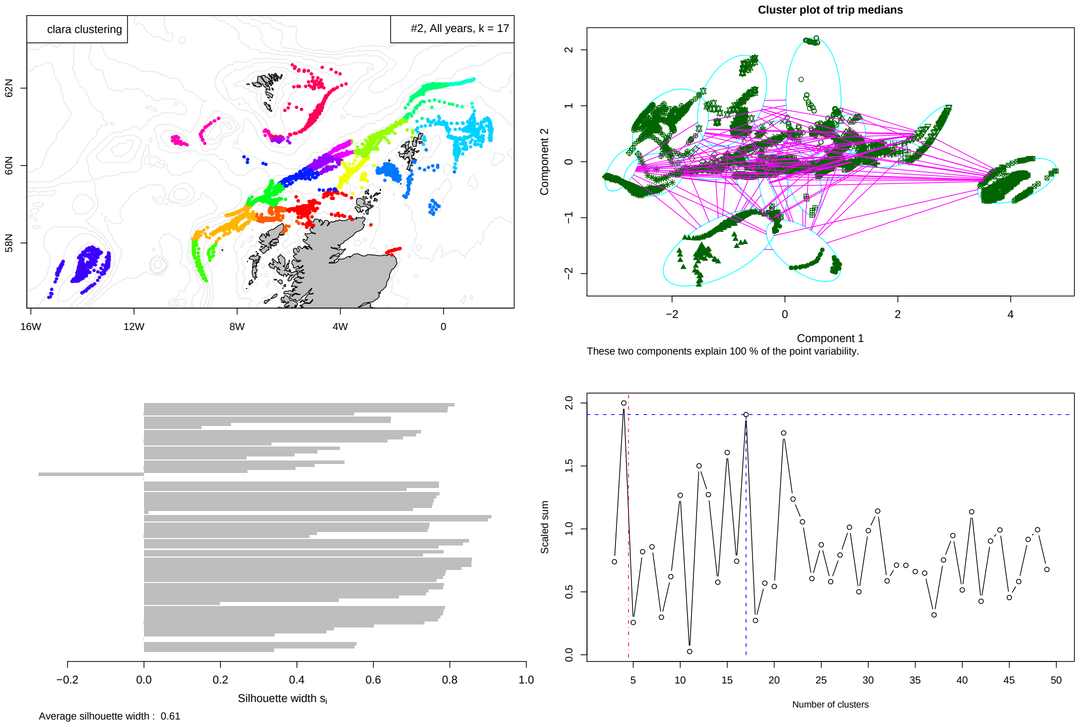


Figure 14.9: CLARA method diagnostics for cluster analysis of VMS data from Vessel 2, assuming $k = k_{\max} = k_{\text{sum}} = 17$. Upper left: VMS pings for Vessel 2 (2008-10), coloured according to cluster membership. Upper right: the clusplot for the analysis (see Section 13.2 for a description). Symbols are the VMS points rescaled to lie on principal component axes. Each ellipse encloses all the rescaled observations from a given cluster, while lines are intended to indicate distance between clusters. Lower left: silhouette widths (see caption for Figure 14.2 for details). Lower right: scaled sums ρ_k (see caption for Figure 14.3 for details.)

14.3 Changes in fishing locations over time

Having determined the fishing locations used by a given vessel during 2008-2010, the next question is whether the frequency with which these locations have been used changed during those years. I note first that fishing areas for the majority of vessels are very seasonal. The locations used traditionally during the spring are usually quite different to those used in the summer, for example, due to factors like improved weather, changes in markets through the year, and availability (or otherwise) of quota. Figure 14.10 demonstrates this succinctly for Vessel 1, which (during 2008-2010) fished at Rockall in the first half of the year only, and fished the Norwegian Deeps (eastern North Sea, towards the Skagerrak) in the second half of the year only. Another good example in the past was the Scottish Rockall haddock fishery (Newton et al. 2008). Historically, this was only ever conducted in the summer months when the weather could be expected to be reasonable, although this has changed recently and the Rockall fishery now takes place throughout the year. Figure 14.11 shows this for Vessel 2, which fished at Rockall at some point during all four quarters over 2008-2010. When considering possible changes in fishing locations between years, it is therefore important to ensure comparison between parts of the year which would normally be expected to be similar. In this study, I will compare the first quarter of 2008 with the first quarter of 2009 (and so on). Analysis on a monthly basis would also be possible, although the likelihood of having very small sample sizes or a null dataset is higher when considering months than quarters.

The next step is to evaluate whether the distribution of VMS pings between fishing areas changes *significantly* within a quarter from year to year. These distributions are summarised using the histograms in Figure 14.12 for Vessel 1, and Figure 14.13 for Vessel 2. The left-to-right ordering of the fishing-area ping count data in these histograms is fixed for each vessel so that the fishing area with the most pings over the full 2008-2010 time-period is plotted on the left of each histogram, down to the fishing area with the least pings on the right of each histogram. If the pattern of fishing effort within a quarter did not change from year to year, then the histograms in each column of Figures 14.12 and 14.13 would be the same. That they are not suggests changes in fishing patterns.

I have explored the question of whether these fishing-pattern changes are *significant* or not using three metrics, as follows. Consider the example in Figure 14.14, in which I compare the VMS data in Q1 from 2008 and 2009 for Vessel 1. The first metric given here is the Kolmogorov-Smirnov test (Kolmogorov 1933, Smirnov 1939b, Smirnov 1939a), which I have implemented in R using the algorithm suggested by

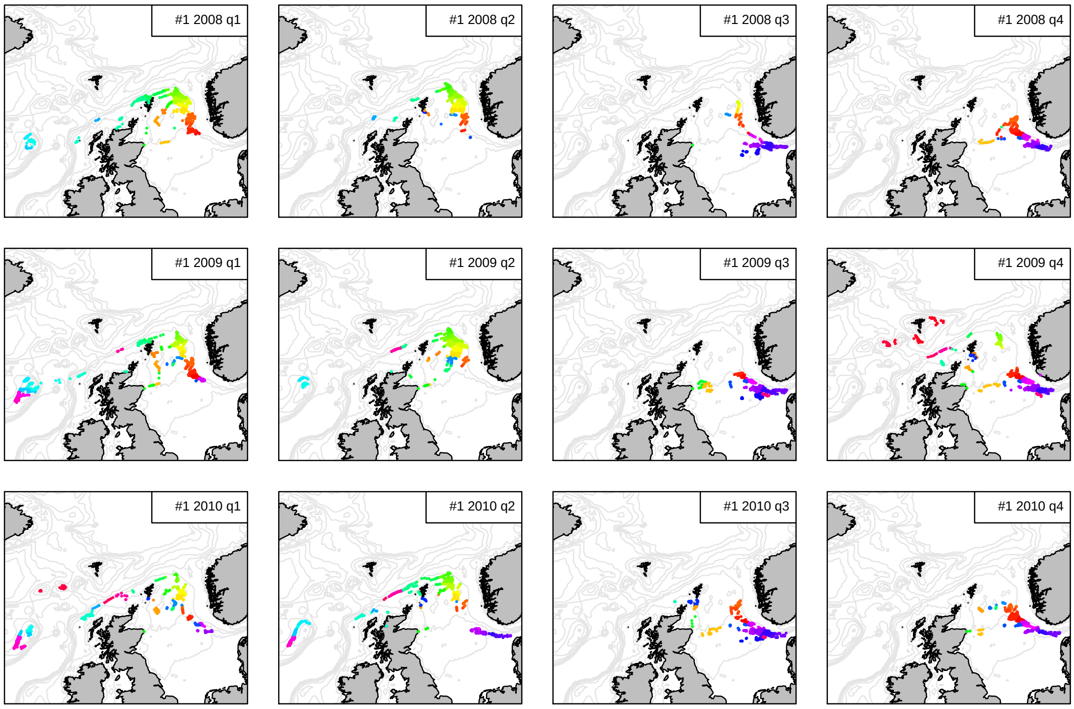


Figure 14.10: VMS points for Vessel 1 during Q1-Q4 and 2008-2010, coloured using the same cluster-membership scheme as in Figure 14.6. Grey lines show bathymetry at 100-m intervals.

Sokal and Rohlf (1995, pages 434–439). Consider two histograms of the same length l, so that

$$H = (h_1, h_2, \ldots, h_l), \quad (14.11)$$

$$G = (g_1, g_2, \ldots, g_l), \quad (14.12)$$

where h_i and g_i are the counts of VMS pings in fishing area i in Q1 for 2008 and 2009, respectively. Form the cumulative sum of each of these histograms,

$$H^* = (h_1^*, h_2^*, \ldots, h_l^*), \quad (14.13)$$

$$G^* = (g_1^*, g_2^*, \ldots, g_l^*), \quad (14.14)$$

where

$$h_i^* = \sum_{j=1}^{i} h_j, \quad (14.15)$$

$$g_i^* = \sum_{j=1}^{i} g_j. \quad (14.16)$$

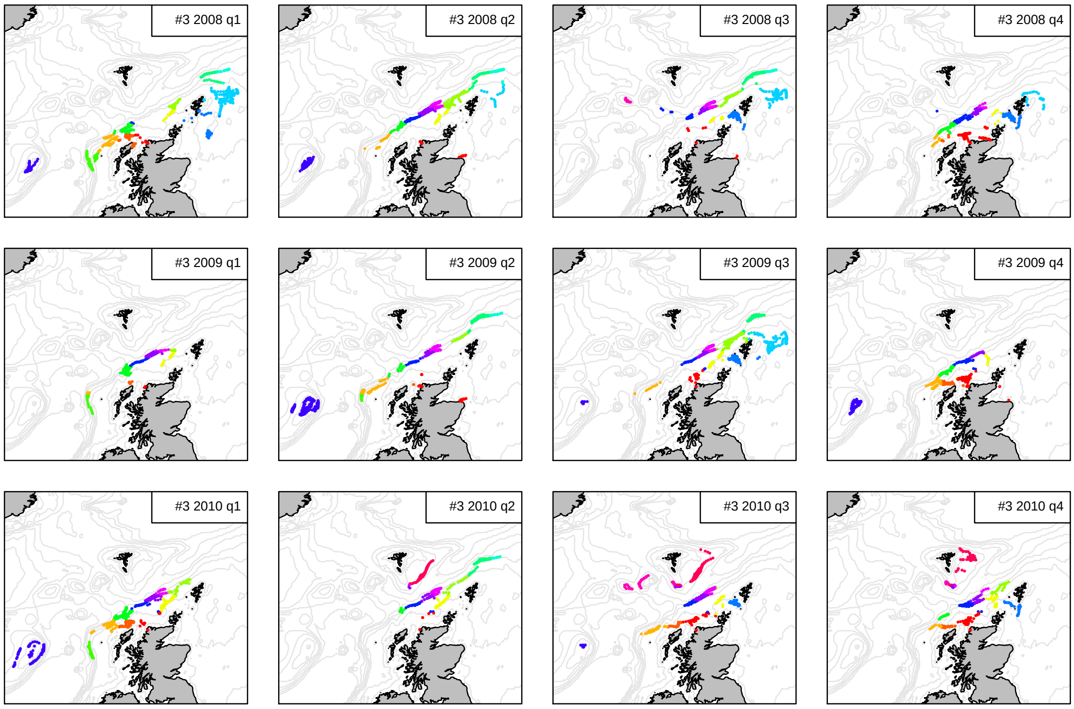


Figure 14.11: VMS points for Vessel 2 during Q1-Q4 and 2008-2010, coloured using the same cluster-membership scheme as in Figure 14.9. Grey lines show bathymetry at 100-m intervals.

If n_H and n_G are the number of pings in H and G, respectively, then the cumulative frequency vectors for each year are

$$H^f = \left(h_1^f, h_2^f, \ldots, h_l^f\right), \tag{14.17}$$

$$G^f = \left(g_1^f, g_2^f, \ldots, g_l^f\right), \tag{14.18}$$

where

$$h_i^f = h_i^* / n_H, \tag{14.19}$$

$$g_i^f = g_i^* / n_G. \tag{14.20}$$

The Kolmogorov-Smirnov test statistic is then

$$D_{\text{ks}} = \max_i \left\{ |h_i^f - g_i^f| \right\} : \tag{14.21}$$

that is, the maximum of the absolute differences between the cumulative histograms. The corresponding two-tailed critical value for significance difference at the α level

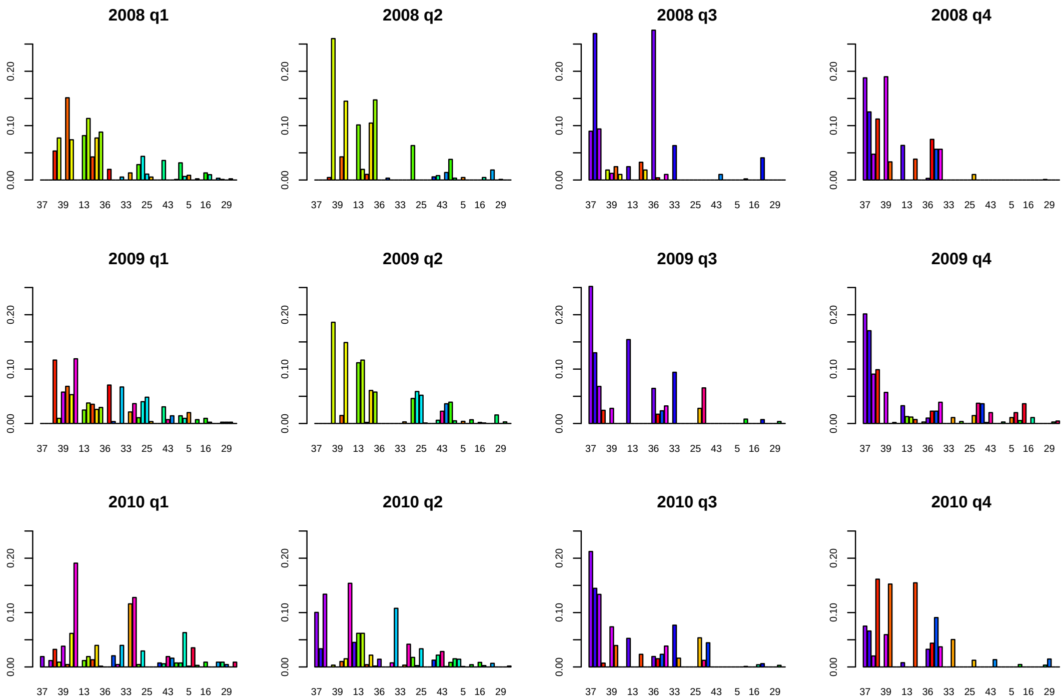


Figure 14.12: Histograms of VMS-ping counts per cluster for Vessel 1, separately for each year (rows) and quarter (columns). Bar colours follow those used for the equivalent clusters in Figures 14.6. Clusters are ordered consistently according to VMS-ping counts over the full 2008-2010 time period.

(Sokal and Rohlf 1995) is then

$$D_{\mathrm{ks},a} = K_a \sqrt{\frac{(n_H + n_G)}{n_H n_G}} \tag{14.22}$$

where

$$K_a = \sqrt{0.5\left[-\log\left(\frac{\alpha}{2}\right)\right]}. \tag{14.23}$$

Figure 14.14 shows the cumulative histograms for Vessel 1, along with the Kolmogorov-Smirnov test results. For this comparison, $D_{\mathrm{ks}} = 0.34$ which is greater than $D_{\mathrm{ks},a} = 0.06$. This suggests that there is a significant difference between years.

However, repeating this comparison for different years, quarters and vessels, I found that the Kolmogorov-Smirnov test statistic nearly *always* suggests a significant difference, even when histograms appear quite similar. To understand why, I applied a randomisation approach (Fisher 1936, Good 1994, and references in Haddon 2001). For this, I consider the VMS pings on the level of the fishing trip. If fishing-location choices were the same in Q1 2008 and Q1 2009 (say), then it would be possible to swap a 2008 fishing trip with a 2009 fishing trip and produce no difference in the

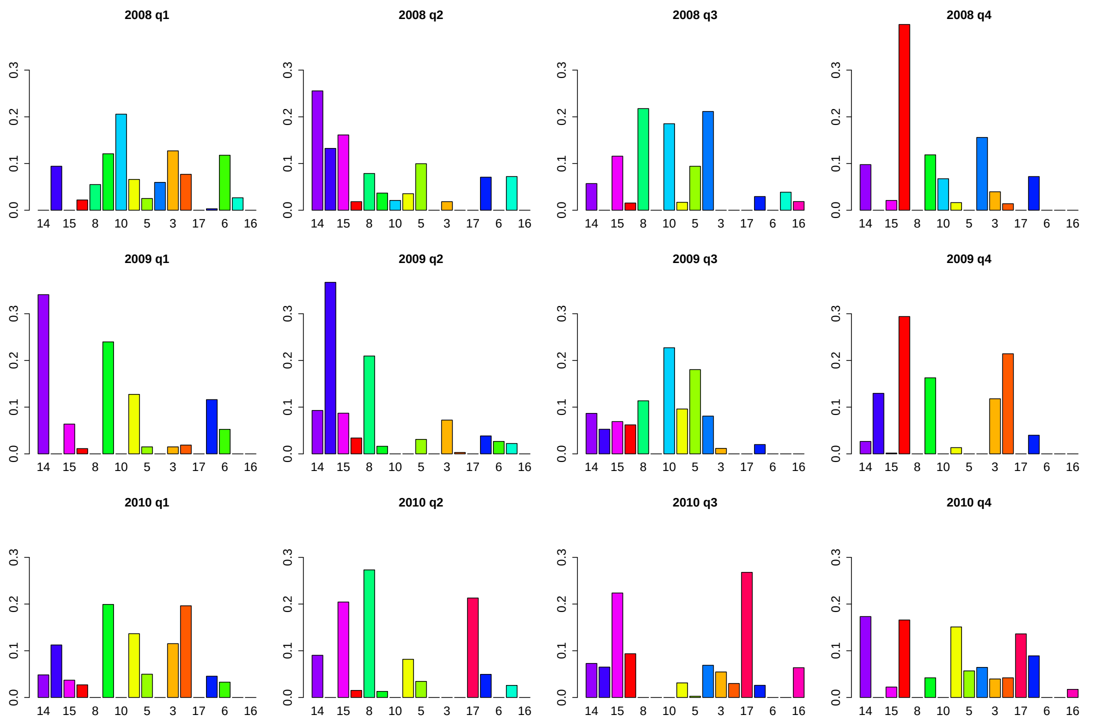


Figure 14.13: Histograms of VMS-ping counts per cluster for Vessel 2, separately for each year (rows) and quarter (columns). Bar colours follow those used for the equivalent clusters in Figures 14.9. Clusters are ordered consistently according to VMS-ping counts over the full 2008-2010 time period.

VMS-ping cluster histograms for the two years (as they would be indistinguishable). In fact, it would be possible to permute fully the trips for the two years and reach the same conclusion.

To implement this for the example in Figure 14.14, I categorised all the VMS pings for both years by trip. I then generated a list of trip ID numbers, of length $n_H + n_G$, and randomly permuted the order of this list. The first n_H permuted trips were then assigned to 2008, the remaining trips to 2009, and the Kolmogorov-Smirnov test statistic was calculated as above. I repeated this process 500 times, to produce a distribution of Kolmogorov-Smirnov test statistics under the hypothesis that the years were *not* different.

This distribution is given in Figure 14.14 (third column, lower row). According to the randomisation approach, if the histograms were significantly different at the $\alpha = 5\%$ level, then the point estimate D_{ks} would be greater than the 95th percentile point of the distribution $D_{\mathrm{ks},95\%}$. In this case, $D_{\mathrm{ks}} = 0.34$ is less than $D_{\mathrm{ks},95\%} = 0.40$, implying that the histograms are *not* significantly different at the 5% level. It seems that in this case, the Kolmogorov-Smirnov significant level $D_{\mathrm{ks},a}$ is too low, as nearly all of the D distribution lies above it. This is generally the case (see Figures 14.14

to 14.17) and would appear to be the reason why the Kolmogorov-Smirnov test nearly always finds a significant difference between these histograms. It is not clear yet *why* this should be, but I hypothesise that the Normal distributional assumption of the test is not being met by these data.

Aside from the statistical properties of the Kolmogorov-Smirnov test, there is also the question of whether the difference metric being used is the correct one. The metric is that given in Equation 14.21, and uses the maximum absolute difference between the cumulative histograms. However, this really only measures the difference in ping counts for one cluster (the one with the maximum difference): all the other clusters could be identical, and the metric in Equation 14.21 would still (possibly even with randomisation) lead to a false conclusion of significant differences.

When viewing VMS ping plots, the eye is very much drawn to differences in outlying clusters, rather than what might constitute the bulk of the pings. Thus, if a vessel had two trips to Rockall one year and not the next, both the eye and the Kolmogorov-Smirnov test might conclude that the years were very different, whereas in fact most of the fishing areas could have remained constant. Care therefore needs to be taken over the distance metric used.

I have examined two alternatives. The first, which I call the presence/absence (PA) function, operates in much the same way, but replaces the difference metric in Equation 14.21 with

$$D_{\mathrm{pa}} = \frac{1}{n_c} \sum_{i=1}^{n_c} d_{\mathrm{pa},i} \tag{14.24}$$

where n_c is the number of clusters, and

$$d_{\mathrm{pa},i} = \begin{cases} 1, & \left\{h_i^f = 0\right\} \oplus \left\{g_i^f = 0\right\} \\ 0, & \text{otherwise} \end{cases} \tag{14.25}$$

Here $\oplus$ is the exclusive-OR operator. In other words, D_{pa} is proportion of clusters which have zero pings in one year and non-zero pings in the next year (or *vice versa*). There is no distributional significance test for this test statistic, but I can apply the same randomisation test as above to determine whether the histograms are significantly different on the basis of a presence/absence test.

The D_{pa} test when comparing 2008 and 2009 ping distributions for Vessel 1 in Q1 is shown in the fourth column (top row) of Figure 14.14. Here the conclusion is the same as for the randomisation-test version of D_{ks}: namely, there is no significant difference. However, Figures 14.15 to 14.17 demonstrate the drawback of D_{pa}: it is derived from a count, and so only ever takes one of the n_c possible values between 0 and 1 during randomisation. Hence the distribution of D_{pa} is not continuous, and it often happens (as in Figures 14.16 to 14.17) that the point estimate of D_{pa} is exactly equal to the 95th distribution percentile $D_{\text{pa},95\%}$. This is not desirable as it limits interpretability.

For this reason, I have developed to a third distance-metric option and will use it as the basis for analysis for the rest of this Chapter. This metric measures the mean absolute difference (AD) between the cumulative histograms,

$$D_{\text{ad}} = \frac{1}{n_c} \sum_{i=0}^{n_c} \left\{ |h_i^f - g_i^f| \right\}. \qquad (14.26)$$

This accounts for differences in all clusters (unlike D_{ks}), and produces continuous distributions following randomisation (unlike D_{pa}). Figures 14.14 to 14.17 show that, according to D_{ad}, the ping cluster-count histograms for Vessel 1 were significantly different between 2008 and 2009 for Q2 and Q3, but not for Q1 or Q4. The results for the first three quarters concur with what would be concluded following a visual inspection of the pings. The fishing areas used in Q1 do look very similar, while quite clear differences exist for Q2 and Q3. A simple confirmation of the visual conclusion does not always arise, however: the pings for Q4 (Figure 14.17) look quite different, but the D_{ad} test suggests no significant difference. In this case, the eye is drawn to the new areas to the north and west used in 2009 but not 2008: however, the bulk of the pings are in the central and eastern North Sea, and these areas do not change much between those two years.

Having developed the method, I applied it to all 188 relevant vessels in the dataset. Out of 1504 histogram comparisons (188 vessels $\times$ 4 quarters $\times$ 2 "years"; 2008-2009 and 2009-2010), the AD method indicated significantly different VMS-ping distributions on 452 occasions (that is, 30.1%). Hence, almost one-third of comparisons showed significant differences. The proportions differ between quarters and between years: Table 14.2 demonstrates that fishing-area changes did not differ much between years, but that vessels were much more likely to change fishing locations in the second half of each year (35% of comparisons on average) than the first (25%). This is not unexpected, since fish quotas for many vessels will only start to become restrictive in the second half of the year. This could lead to the observed changes in fishing locations if skippers are trying to avoid aggregations of a species for which they have little or no quota remaining.

It is also instructive to consider whether there is any discernable difference between vessels in terms of changes in fishing distribution between years. Table 14.3 summarises the results of the AD analysis by vessel. The number of significant dif-

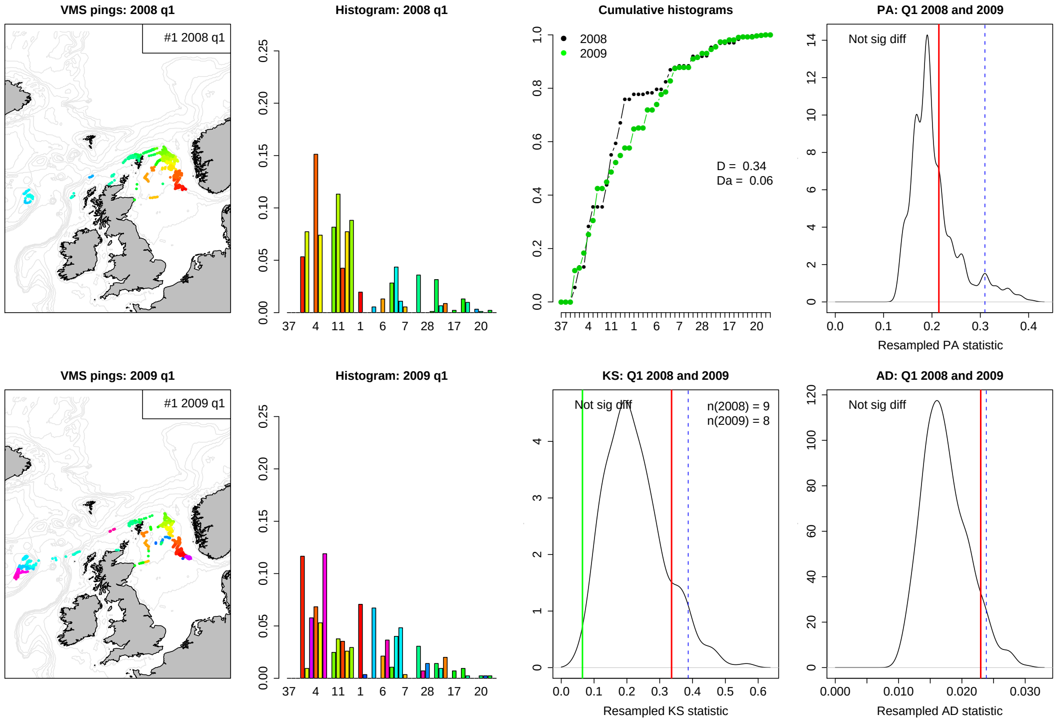


Figure 14.14: Histogram analysis for Vessel 1, comparing Q1 VMS data for 2008 and 2009. First column: VMS points for Vessel 1 during Q1 in 2008 (upper) and 2009 (lower), coloured using the same cluster-membership scheme as in Figure 14.6. Second column: histograms of VMS-pin counts per cluster, during Q1 in 2008 (upper) and 2009 (lower) (coloured as for the first column). Third column (upper): cumulative histograms for Q1 2008 (black) and Q1 2009 (green). D and Da are the Kolmogorov-Smirnov test statistic and significance level, respectively. Third column (lower): distribution of resampled Kolmogorov-Smirnov test statistics (see text for details). Lines give the KS significant value D_a (green), the KS test statistic D (red), and the upper 95th percentile of the distribution (blue). Legends indicate whether the test is significant, and the number of trips in 2008 and 2009 respectively. Fourth column: distributions of resampled PA (upper) and AD (lower) test statistics (see text for details).

ferences ranged from 0 (21 vessels, or 11%) to 7 (3 vessels, or 2%). Of the vessels which showed no significant changes, 12 (57%) were vessels targetting *Nephrops* in the Fladen, Moray Firth or South Minch grounds. The vessels with the most changes are not readily classifiable, and include a mixed-species trawler fishing along the shelf edge, a *Nephrops* vessel covering a wide range of (mostly western) inshore grounds, and a mixed-species trawler operating around Shetland. There may of course be many reasons why a vessel would or would not change fishing area for a quarter from year to year (and I will consider the effects of RTCs in Section 14.5), but it is interesting to note that more than half of the vessels which did *not* change could be classified as *Nephrops* vessels fishing on the principal Scottish *Nephrops* grounds, which may be because they are not directly targetting cod.

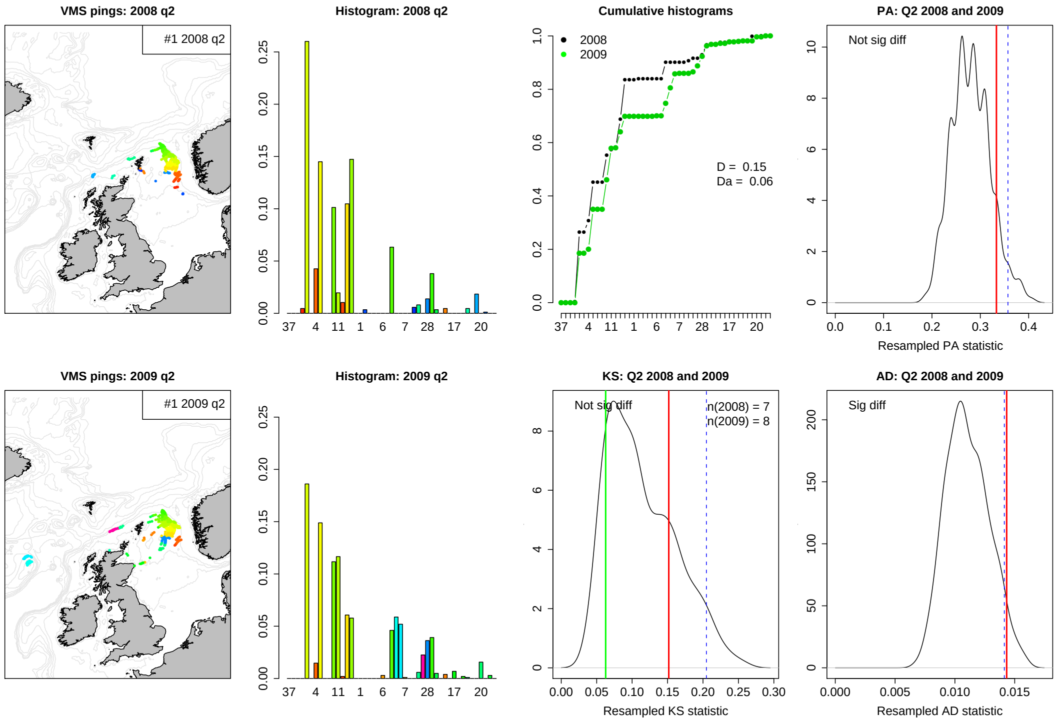


Figure 14.15: Histogram analysis for Vessel 1, comparing Q2 VMS data for 2008 and 2009. See caption for Figure 14.14 for details.

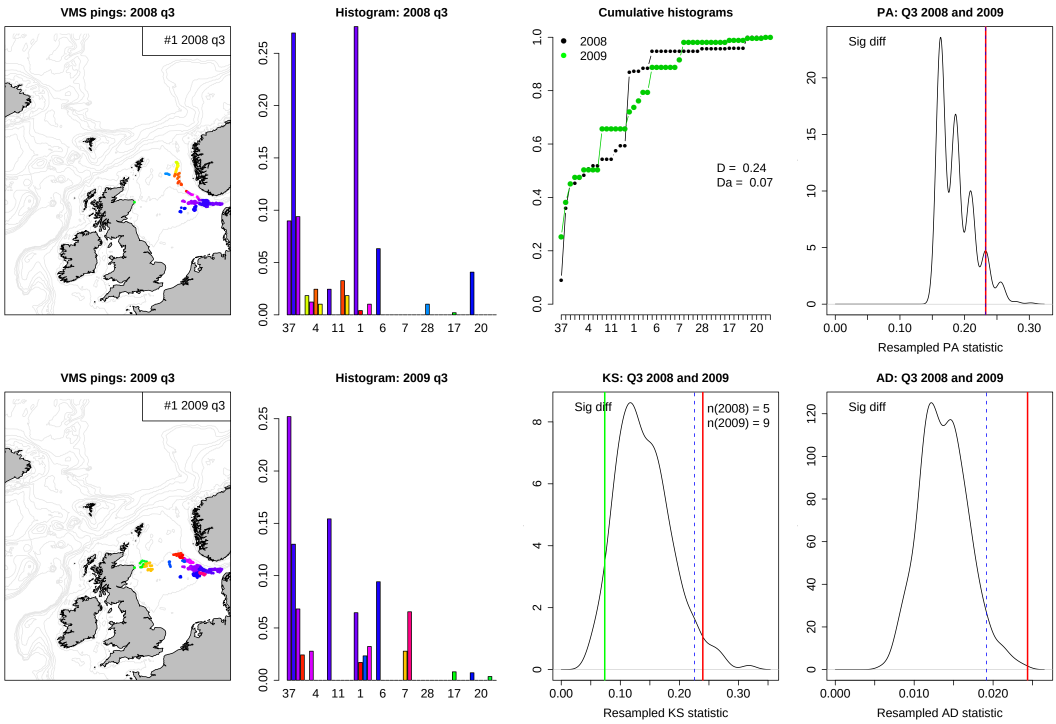


Figure 14.16: Histogram analysis for Vessel 1, comparing Q3 VMS data for 2008 and 2009. See caption for Figure 14.14 for details.

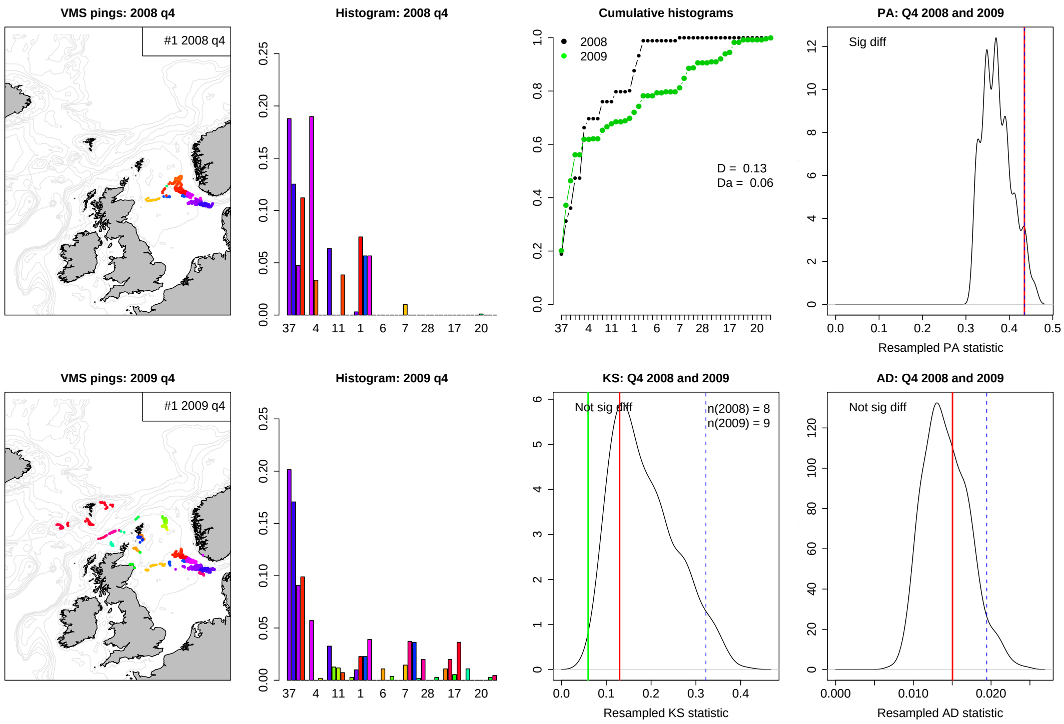


Figure 14.17: Histogram analysis for Vessel 1, comparing Q4 VMS data for 2008 and 2009. See caption for Figure 14.14 for details.

	Quarter				
Year	1	2	3	4	Marginal totals
2008-2009	57 (30%)	38 (20%)	66 (35%)	73 (39%)	234 (31%)
2009-2010	44 (23%)	48 (26%)	69 (37%)	57 (30%)	218 (29%)
Marginal totals	101 (27%)	86 (23%)	135 (36%)	130 (35%)	

Table 14.2: Numbers of vessels with significant differences between VMS-ping distributions, as measured by the AD method, categorised by year (2008-2009, 2009-2010) and quarter. The total number of comparisons for each combination of year and quarter was 188.

V	SD	V	SD	V	SD	V	SD
1	4	48	2	95	2	142	6
2	2	49	3	96	4	143	2
3	1	50	2	97	2	144	4
4	1	51	6	98	1	145	4
5	1	52	1	99	2	146	5
6	1	53	4	100	1	147	0
7	2	54	5	101	3	148	4
8	6	55	2	102	2	149	1
9	2	56	3	103	3	150	3
10	1	57	1	104	0	151	0
11	1	58	5	105	0	152	4
12	0	59	2	106	4	153	2
13	4	60	2	107	2	154	2
14	4	61	2	108	6	155	5
15	5	62	2	109	1	156	4
16	4	63	2	110	1	157	1
17	2	64	2	111	1	158	0
18	3	65	2	112	6	159	1
19	2	66	3	113	3	160	2
20	0	67	6	114	4	161	3
21	3	68	5	115	2	162	0
22	1	69	2	116	1	163	5
23	3	70	1	117	5	164	2
24	1	71	3	118	2	165	2
25	3	72	2	119	1	166	7
26	3	73	5	120	0	167	1
27	2	74	1	121	7	168	1
28	1	75	1	122	5	169	1
29	1	76	1	123	0	170	0
30	7	77	5	124	1	171	2
31	2	78	2	125	5	172	3
32	2	79	0	126	3	173	2
33	5	80	0	127	1	174	2
34	6	81	1	128	1	175	3
35	0	82	0	129	1	176	5
36	4	83	2	130	2	177	3
37	1	84	1	131	3	178	0
38	1	85	0	132	4	179	1
39	5	86	0	133	3	180	1
40	4	87	3	134	3	181	1
41	1	88	4	135	5	182	3
42	1	89	1	136	5	183	1
43	3	90	1	137	4	184	4
44	4	91	6	138	0	185	3
45	2	92	0	139	3	186	4
46	0	93	1	140	1	187	2
47	2	94	1	141	3	188	1

Table 14.3: Significant differences between VMS-ping distributions, as measured by the AD method, categorised by vessel. V = vessel, SD = number of significant differences (out of a possible total of eight: 2 years $\times$ 4 quarters).

14.4 Changes in RTC density per fishing area over time

I have demonstrated a method for determining whether a vessel changes its distribution of fishing areas for a given quarter from one year to the next, using VMS data from 2008-2010 for a 188-vessel subset of the Scottish fishing fleet. In this Section, I consider whether such changes can be linked (if only in a correlational sense) to the implementation of RTCs in those same fishing areas.

Figure 14.18 summarises the RTCs imposed by the Scottish Government during years 2008-2010, and for each quarter thereof. There were very few RTCs in 2008, but the pattern for 2009 and 2010 was quite consistent with more RTCs in the second and third quarters than the first or fourth. The distribution of RTCs is similar to the cod distribution generated in Section 11.2 (see, for example, Figure 11.9). Finally, the RTCs generally increase in area for the third and fourth quarters of 2010, following an increase in the permitted maximum from 50 to 225 square nautical miles (see page 141).

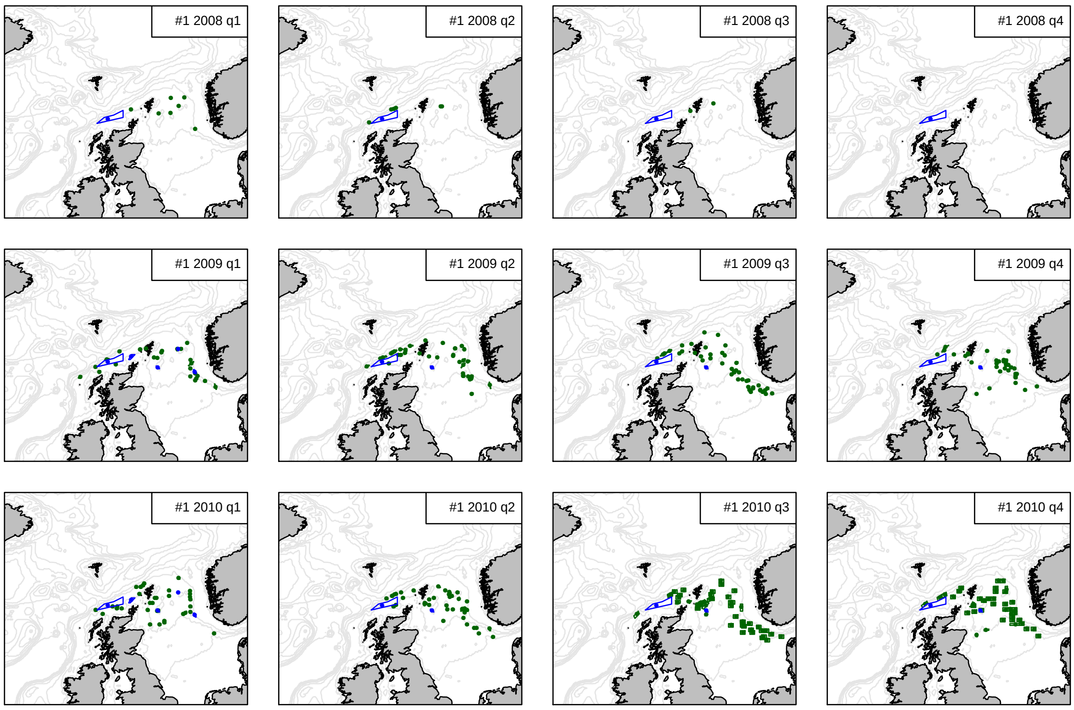


Figure 14.18: Scottish real-time closures (RTCs) for quarters Q1-Q4, during years 2008-2010. The RTCs are marked as green polygons, overlaid with a green symbol that marks the centroid of each RTC. Seasonal and other more permanent closures are marked by blue polygons. Grey lines show bathymetry at 100-m intervals.

Given this distribution of RTCs, I can now count how many RTCs fall within the boundaries of the fishing areas for each vessel (as determined by the cluster-analysis approach described in Section 14.2). Figures 14.19 to 14.21 summarise these counts for Vessels 1 and 2 from the dataset of relevant Scottish fishing vessels. In this analysis, I summarise each RTC by its geographic midpoint, and count the number of such midpoints that occur in each fishing area for that vessel during the year and quarter concerned. For RTCs that span the change from one quarter to the next, I have used only the first such quarter by assigning each midpoint to the first date of the RTC duration. These simplifications facilitate the analysis, although reducing each RTC to its midpoint may introduce some bias in the second half of 2010 when RTCs became considerably larger. It could be argued that an RTC of 225 square nautical miles would be more likely to induce changes in fishing area than one of 50 square nautical miles, but I have not explored this possibility here. For both Vessels 1 and 2, the presence of RTCs in their fishing areas increases substantially from 2008 to 2010.

As before, I generated these counts for all 188 relevant vessels in the Scottish dataset. Results are given in Table 14.4. In all cases, the number of RTCs in fishing areas increased or (rarely) stayed the same from 2008 to 2009, while this occurred from 2009 to 2010 for 181 vessels (96.3%). While this is to be expected, given the rapid increase in the number of RTCs from 2008 onwards, the fact that RTC numbers increased in the fishing areas of nearly all relevant vessels suggests that relating fishing-location changes to increases in local RTC numbers may have some validity. I explore this possibility in Section 14.5.

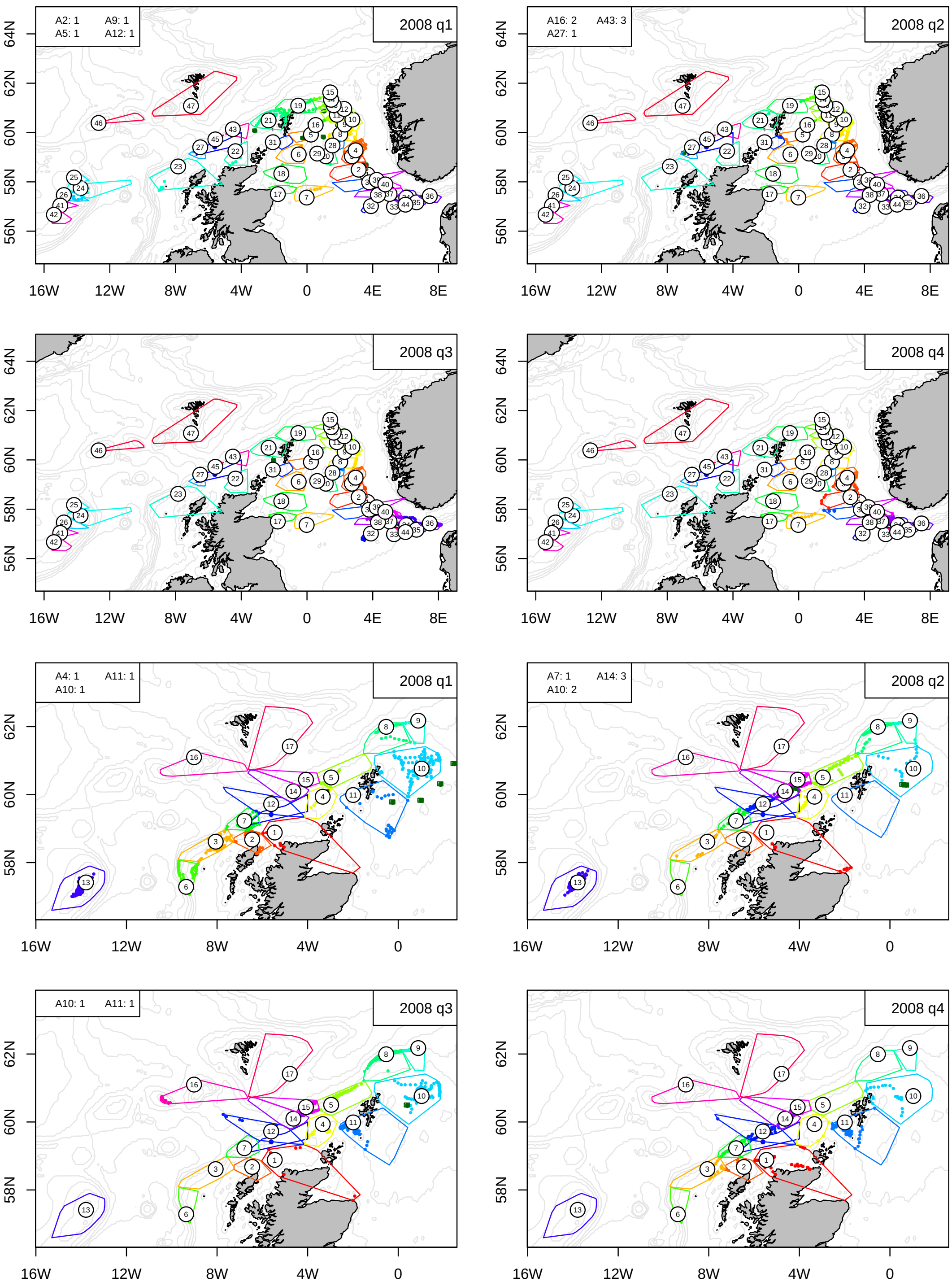


Figure 14.19: Number of RTC midpoints in each cluster of Vessels 1 (upper four plots) and 2 (lower four plots) during 2008. The RTCs are marked as green polygons, overlaid with a green symbol that marks the centroid of each RTC. Seasonal and other more permanent closures are marked by blue polygons. VMS points are coloured using the same cluster-membership scheme as in Figures 14.6 and 14.9. Grey lines show bathymetry at 100-m intervals. The legend (top left) shows the counts of RTC medians in each cluster (for non-zero counts only).

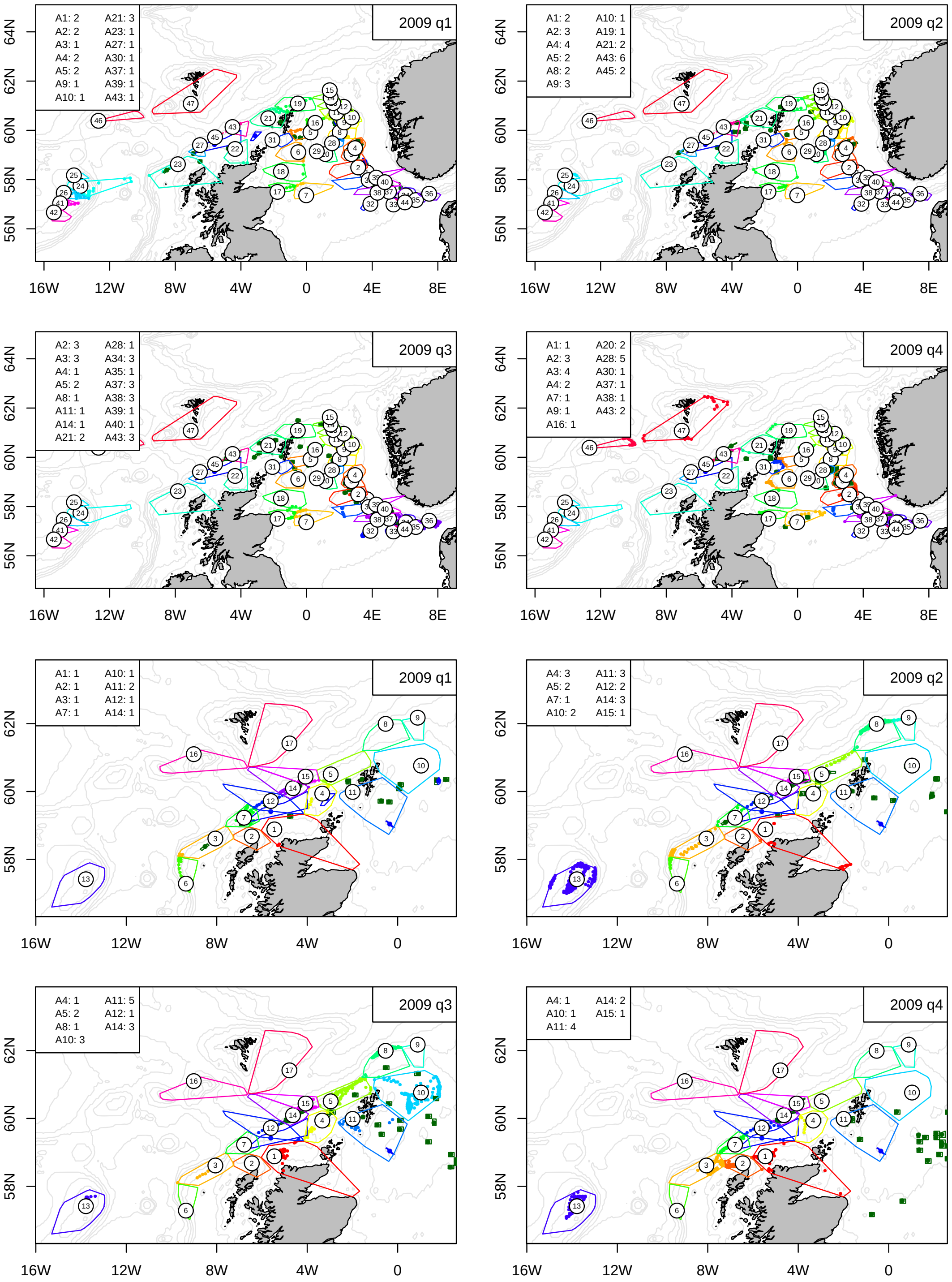


Figure 14.20: Number of RTC midpoints in each cluster of Vessels 1 (upper four plots) and 2 (lower four plots) during 2009. See caption for Figure 14.19 for details.

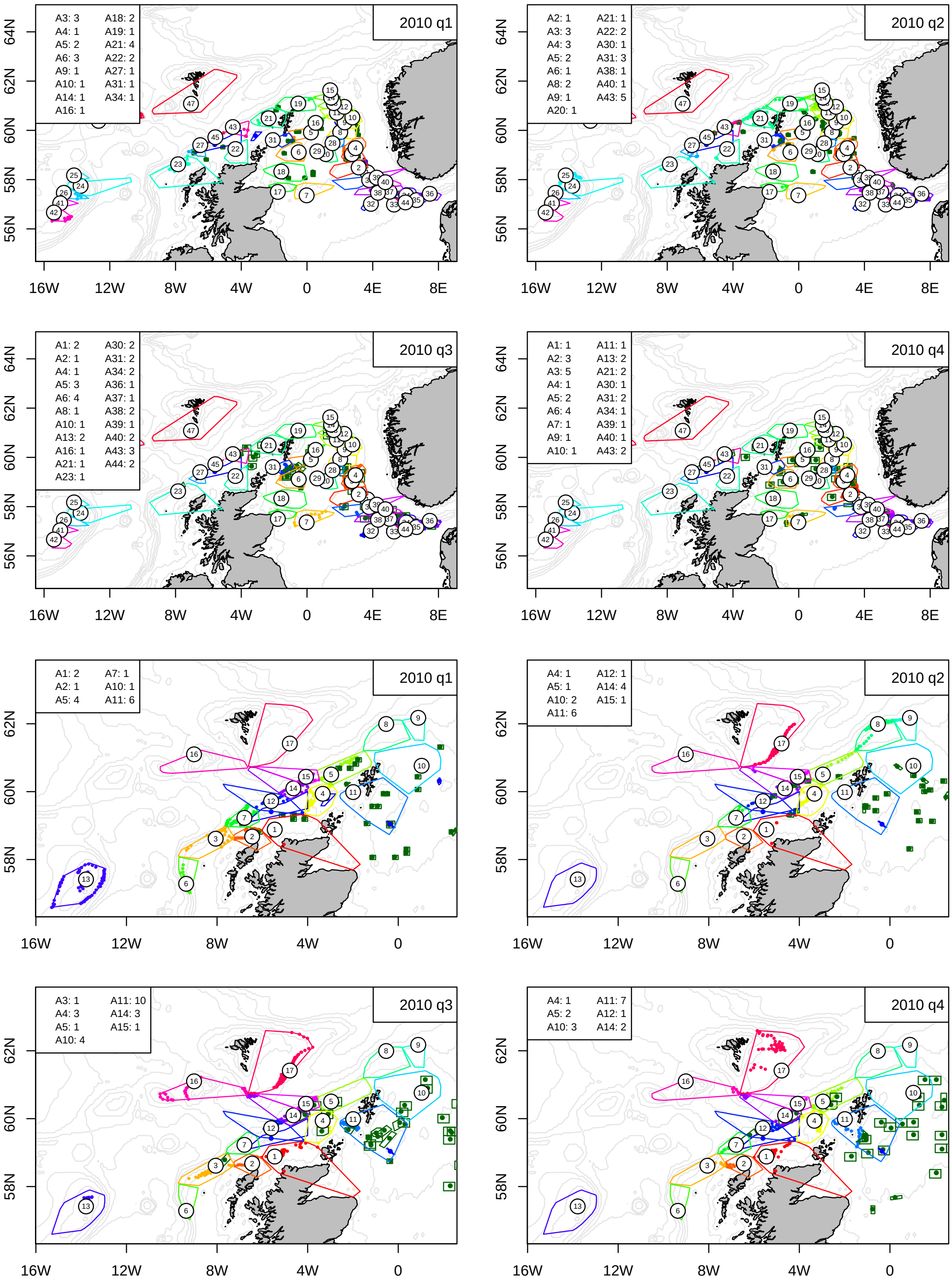


Figure 14.21: Number of RTCs medians in each cluster of Vessels 1 (upper four plots) and 2 (lower four plots) during 2010. See caption for Figure 14.19 for details.

V	08	09	10	V	08	09	10	V	08	09	10	V	08	09	10
1	10	103	121	48	5	24	47	95	0	0	10	142	11	87	112
2	11	51	70	49	7	65	91	96	8	31	57	143	1	8	20
3	9	32	31	50	12	56	90	97	1	3	19	144	2	12	37
4	9	45	53	51	0	1	2	98	0	0	10	145	5	18	31
5	12	92	120	52	7	67	67	99	0	4	3	146	0	0	1
6	13	85	111	53	12	97	120	100	0	0	11	147	0	0	8
7	8	36	48	54	7	45	71	101	0	0	8	148	0	1	7
8	11	103	123	55	8	36	67	102	0	2	12	149	0	2	15
9	4	13	42	56	0	0	1	103	0	2	3	150	0	0	10
10	14	113	131	57	1	5	10	104	0	0	10	151	0	0	7
11	4	34	73	58	6	43	63	105	0	1	10	152	1	11	23
12	6	92	109	59	4	38	54	106	6	17	37	153	2	4	35
13	9	43	48	60	9	42	79	107	4	19	39	154	7	26	52
14	4	19	22	61	10	98	114	108	0	2	6	155	7	27	41
15	6	42	69	62	12	109	129	109	1	14	14	156	0	1	3
16	9	86	110	63	12	106	114	110	0	0	7	157	0	0	6
17	6	44	66	64	10	48	72	111	4	16	29	158	0	8	0
18	6	31	65	65	4	30	44	112	1	2	16	159	1	13	14
19	6	19	25	66	5	47	58	113	3	18	24	160	8	33	51
20	5	73	79	67	2	19	26	114	0	0	4	161	5	37	64
21	8	90	113	68	12	58	84	115	0	1	6	162	7	31	39
22	1	8	35	69	6	23	55	116	0	0	9	163	8	27	54
23	7	34	32	70	5	41	50	117	8	53	84	164	3	12	27
24	11	53	76	71	5	35	36	118	3	7	19	165	6	31	62
25	8	94	106	72	0	0	0	119	0	2	16	166	0	5	11
26	10	79	93	73	8	87	111	120	0	2	16	167	8	66	88
27	2	5	30	74	6	32	40	121	0	1	2	168	4	37	44
28	0	0	10	75	10	49	63	122	8	43	59	169	6	73	74
29	5	20	48	76	2	17	42	123	3	6	20	170	9	36	51
30	10	38	45	77	6	20	42	124	0	0	9	171	6	62	80
31	9	87	108	78	0	1	9	125	7	73	96	172	15	125	157
32	12	60	83	79	1	8	15	126	1	5	24	173	14	121	147
33	8	63	81	80	0	0	9	127	8	66	88	174	9	40	38
34	11	31	55	81	0	0	10	128	2	14	33	175	5	19	25
35	9	72	85	82	0	0	8	129	0	2	13	176	5	22	34
36	9	41	62	83	0	2	7	130	6	19	42	177	0	2	13
37	4	18	38	84	0	0	2	131	13	53	75	178	1	6	2
38	14	133	143	85	0	0	11	132	9	40	68	179	5	22	51
39	8	75	95	86	0	0	13	133	0	3	15	180	0	0	1
40	6	44	50	87	2	6	20	134	7	28	46	181	0	2	11
41	7	51	58	88	0	0	2	135	0	2	10	182	2	3	16
42	13	116	128	89	0	0	3	136	7	25	44	183	9	96	108
43	7	31	43	90	3	6	17	137	7	20	46	184	0	0	3
44	4	32	44	91	1	2	14	138	0	2	16	185	8	54	65
45	7	31	34	92	0	7	18	139	5	12	10	186	4	14	36
46	13	114	120	93	0	0	0	140	0	0	7	187	2	5	21
47	10	50	57	94	4	10	24	141	5	15	39	188	1	6	19

Table 14.4: Counts of RTC centroids in the fishing areas of each relevant vessel (V) for 2008–2010.

14.5 Relating fishing location changes to RTC density

The final step in this analysis is to determine whether there is a relationship between changes in fishing areas used over time, and changes in the density of RTCs in those areas. Although I will carry out this study using the fleet as a whole, the component parts of the analysis are built up from data on individual vessels, as follows.

14.5.1 *Individual vessels*

Consider Vessel i from the dataset of $I = 188$ relevant vessels. The cluster analysis presented in Section 14.2 generates estimates of k_i distinct fishing areas for Vessel i, indexed by $\mathbf{n} = (n_1, n_2, \ldots, n_{k_i})$. For each fishing area n_j, quarter $(q \in \{1,2,3,4\})$ and year comparison $(yc \in \{2008-2009, 2009-2010\})$, Section 14.3 provides a measure of the difference between VMS ping counts from one year to the next, given by

$$d^v_{i,j,q,yc} = v_{i,j,q,y+1} - v_{i,j,q,y}, \tag{14.27}$$

where $v_{i,j,q,y}$ is the VMS ping count for Vessel i, fishing area j, and quarter q, and $y =$ 2008 or 2009 as required. The method presented in Section 14.4 gives a corresponding measure of the difference between the RTC counts

$$d^r_{i,j,q,yc} = r_{i,j,q,y+1} - r_{i,j,q,y}, \tag{14.28}$$

where $r_{i,j,q,y}$ is the corresponding RTC count. These could be compared directly, through regression or contingency-table analyses, but I observe that for a given vessel i, quarter q and year comparison yc, the AD method (Section 14.3) indicates whether the ping distributions across all fishing areas $\mathbf{n}$ are *significantly* different from one year to the next. Therefore I also use the AD-method indication to strip out all those $\left(d^v_{i,j,q,yc}, d^r_{i,j,q,yc}\right)$ points for which ping distributions are not significantly different.

The first approach I tried was regression analysis, using count data from vessels individually. Figures 14.22 to 14.25 illustrate results for the first two vessels in the relevant dataset, and also indicate the principal drawback with this approach. When considering a single vessel, the AD-method histogram comparison may not be significant (so that no valid conclusions can be drawn), or there may be too many instances of $d^v_{i,j,q,yc} = 0$ or $d^r_{i,j,q,yc} = 0$ (or both) for a regression analysis to be successful. Figures 14.22 to 14.25 demonstrate this well, and show that no clear inference about the relationship between RTC count difference and ping count difference can be made using regression analysis at the scale of the single vessel.

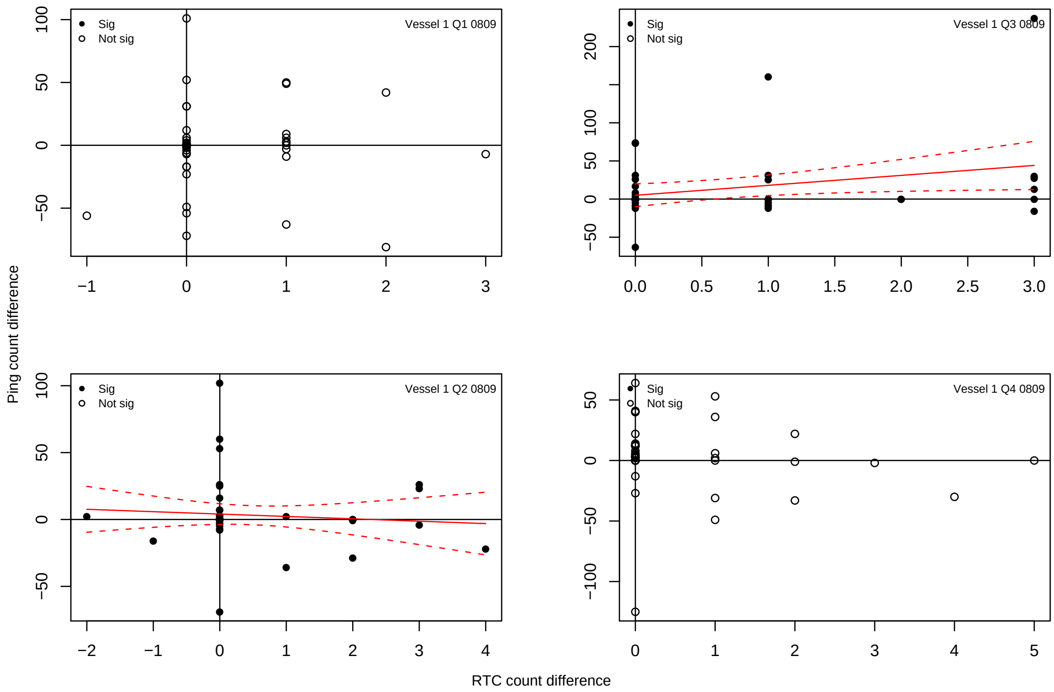


Figure 14.22: Regression analyses comparing ping count difference $d^v_{i,j,q,yc}$ and RTC count difference $d^r_{i,j,q,yc}$ between 2008 and 2009 for Vessel 1. Plots for quarters with significantly different fishing distributions by the AD test use filled circles, otherwise open circles are used. For quarters passing the AD test, red lines give fitted linear models (solid) with 95% confidence intervals (dashed).

My second approach used contingency-table analysis, and for single-vessel comparisons this suffers from a similar drawback. For each combination of vessel i, year comparison yc and quarter q, I constructed a contingency table T in which both ping count difference and RTC count difference are categorised as being negative, zero or positive:

$$T_{i,q,yc} = \left[\begin{array}{cccc} & d^v_{i,j,q,yc} < 0 & d^v_{i,j,q,yc} = 0 & d^v_{i,j,q,yc} > 0 \\ d^r_{i,j,q,yc} < 0 & T^{1,1}_{i,q,yc} & T^{1,2}_{i,q,yc} & T^{1,3}_{i,q,yc} \\ d^r_{i,j,q,yc} = 0 & T^{2,1}_{i,q,yc} & T^{2,2}_{i,q,yc} & T^{2,3}_{i,q,yc} \\ d^r_{i,j,q,yc} > 0 & T^{3,1}_{i,q,yc} & T^{3,2}_{i,q,yc} & T^{3,3}_{i,q,yc} \end{array} \right]$$

For example, $T^{1,1}_{i,q,yc}$ gives the count of the fishing areas for vessel i for which the ping count difference $d^v_{i,j,q,yc}$ and the RTC count difference $d^r_{i,j,q,yc}$ (across all fishing areas j) were both negative. Once this table is constructed, I apply Pearson's χ^2 test to determine whether the proportion of counts between different columns changes signif-

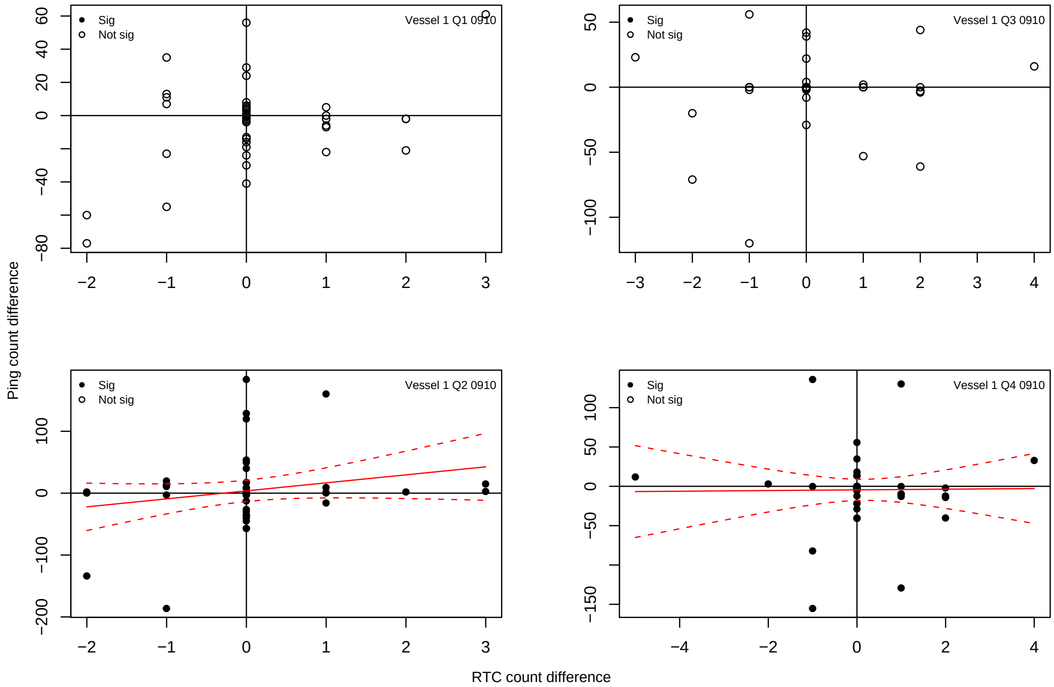


Figure 14.23: Regression analyses comparing ping count difference $d^v_{i,j,q,yc}$ and RTC count difference $d^r_{i,j,q,yc}$ between 2009 and 2010 for Vessel 1. See caption for Figure 14.22 for details.

icantly ($p < 0.05$) between rows. If so, then there is a *contingency* between the two variables (that is, the two variables are not independent), and ping counts are deemed to be significantly influenced by RTC counts. If there is no contingency, the two variables are independent, and ping counts are not significantly influenced by RTC counts. χ^2 tests were carried out in R, using the `chisq.test` function of the `stats` library.

Consider two extreme examples to demonstrate the expected output. In table τ_1, all the entries are the same:

$$\tau_1 = \begin{bmatrix} & d^v < 0 & d^v = 0 & d^v > 0 \\ d^r < 0 & 1 & 1 & 1 \\ d^r = 0 & 1 & 1 & 1 \\ d^r > 0 & 1 & 1 & 1 \end{bmatrix}$$

The χ^2 test statistic for τ_1 is 1.0, with 4 degrees of freedom and a p-value of 1.0. This indicates strong independence between the variables and no contingency: that is, knowing the difference in RTC counts d^r would not help us to determine the difference in ping counts d^v. On the other hand, in table τ_2 there appears to be a direct relationship

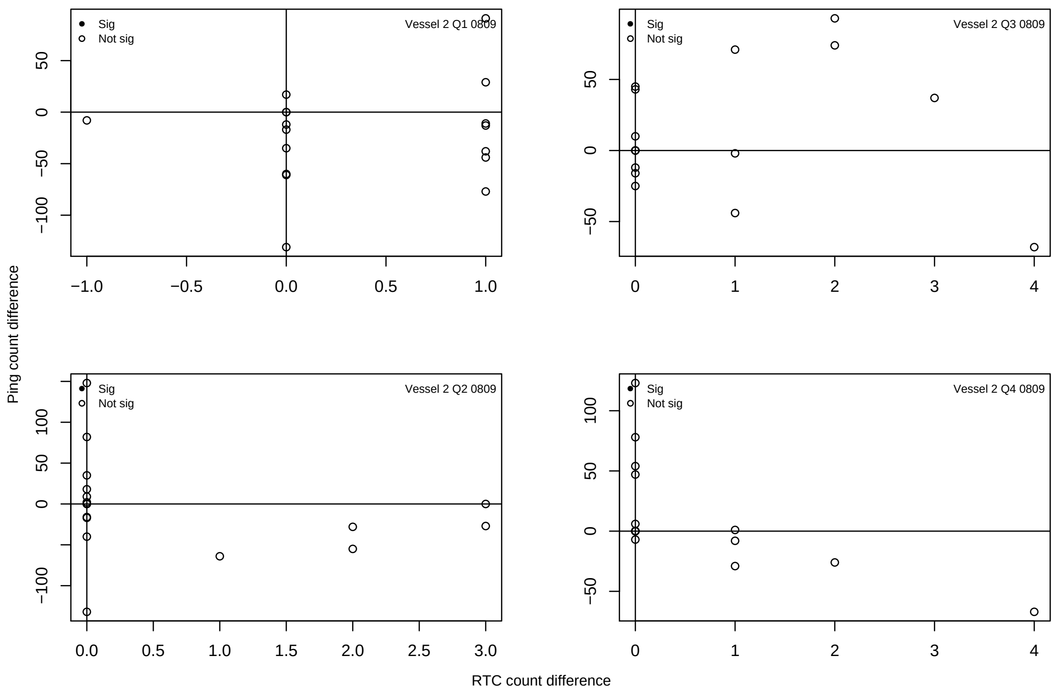


Figure 14.24: Regression analyses comparing ping count difference $d^v_{i,j,q,yc}$ and RTC count difference $d^r_{i,j,q,yc}$ between 2008 and 2009 for Vessel 2. See caption for Figure 14.22 for details.

between the variables:

$$\tau_2 = \begin{bmatrix} & d^v < 0 & d^v = 0 & d^v > 0 \\ d^r < 0 & 10 & 0 & 0 \\ d^r = 0 & 0 & 10 & 0 \\ d^r > 0 & 0 & 0 & 10 \end{bmatrix}$$

In this case, the χ^2 test statistic is 60.0, with 4 degrees of freedom and $p < 1.0e-10$, suggesting strong dependence and hence contingency. Here, knowledge of d^r gives a very strong indication of the sign of d^v.

Returning to the single-vessel analysis, for Vessel 1 there were four histogram comparisons that were significant by the AD test: Q2 and Q3 for 2008-08 (Figure 14.22), and Q2 and Q4 for 2009-10 (Figure 14.23). The corresponding contingency tables and χ^2 test results were as follows.

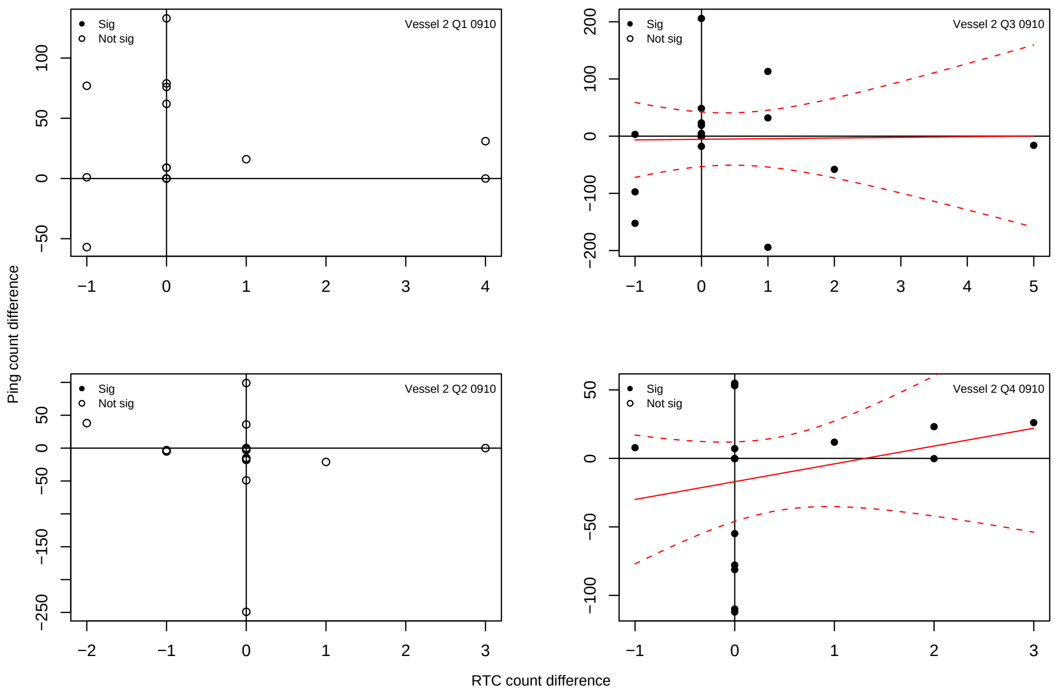


Figure 14.25: Regression analyses comparing ping count difference $d^v_{i,j,q,yc}$ and RTC count difference $d^r_{i,j,q,yc}$ between 2009 and 2010 for Vessel 2. See caption for Figure 14.22 for details.

$$T_{1,2,0809} = \begin{bmatrix} & d^v < 0 & d^v = 0 & d^v > 0 \\ d^r < 0 & 1 & 0 & 1 \\ d^r = 0 & 7 & 16 & 11 \\ d^r > 0 & 5 & 3 & 3 \end{bmatrix} \qquad \begin{array}{l} \chi^2 = 4.166 \\ (\mathrm{df} = 4, p = 0.384 > 0.05) \end{array}$$

$$T_{1,3,0809} = \begin{bmatrix} & d^v < 0 & d^v = 0 & d^v > 0 \\ d^r < 0 & 0 & 0 & 0 \\ d^r = 0 & 4 & 20 & 7 \\ d^r > 0 & 4 & 5 & 7 \end{bmatrix} \qquad \begin{array}{l} \chi^2 = 4.691 \\ (\mathrm{df} = 2, p = 0.096 > 0.05) \end{array}$$

$$T_{1,2,0910} = \begin{bmatrix} & d^v < 0 & d^v = 0 & d^v > 0 \\ d^r < 0 & 3 & 2 & 4 \\ d^r = 0 & 13 & 7 & 10 \\ d^r > 0 & 1 & 1 & 6 \end{bmatrix} \qquad \begin{array}{l} \chi^2 = 4.624 \\ (\mathrm{df} = 4, p = 0.328 > 0.05) \end{array}$$

$$T_{1,4,0910} = \begin{bmatrix} & d^v < 0 & d^v = 0 & d^v > 0 \\ d^r < 0 & 2 & 1 & 5 \\ d^r = 0 & 14 & 11 & 5 \\ d^r > 0 & 8 & 1 & 2 \end{bmatrix} \qquad \begin{array}{l} \chi^2 = 6.683 \\ (\text{df} = 4, p = 0.154 > 0.05) \end{array}$$

It would appear from these results that changes in RTC counts within fishing areas for Vessel 1 do not have a significant relationship with change in VMS ping counts within those same areas, although the χ^2 test for the comparison of 2008 and 2009 in quarter 3 is *almost* significant. This conclusion is contingent on the fact that I have limited the analysis to those inter-year comparisons for which the change in fishing locations was deemed to be significant via the AD test.

If I apply this approach to all 188 relevant vessels individually, it is difficult to detect significant influences. Recall (from page 195) that there were 452 inter-year comparisons for which the AD test indicated significantly different VMS-ping histograms. Following the methodology summarised above, I generated contingency tables comparing changes in VMS ping counts and RTC counts for all 452 cases. For only 25 of these (5.53%) was there a significant influence of changes in RTC counts on changes in VMS ping counts, as measured by contingency-table analysis. It may indeed be the case that the imposition of RTCs in fishing areas has little effect on fishing-location choice, but it is equally possible that the contingency-table approach has little statistical power when applied to individual vessels (the number of counts in the tables is quite low), and the question is worthy of further investigation.

14.5.2 Fleet-level analysis

Given that single-vessel analyses may lack statistical power, I applied the same methodology to a dataset which collated *all* the inter-year comparisons with significant fishing-location changes: that is, as in the previous analysis but summed across all relevant fishing vessels (but still only including those histogram comparisons indicated as being significant via the AD test).

Figure 14.26 gives the scatterplot of ping count difference $d^v_{i,j,q,yc}$ against RTC count difference $d^r_{i,j,q,yc}$ for all of these significant inter-year comparisons, along with a linear-model regression line (analogous to the single-vessel examples in Figure 14.22 to 14.25). The line is well-defined with narrow confidence bounds, but this is due to the large number of points on the plot: in fact, the linear model explains very little of the relationship between the variables ($R^2 = 0.2\%$). The slope of the line is small, but it is significantly positive (slope $= 3.194, p < 0.001$). Thus, on the basis of regression analysis across the fleet as a whole, RTCs have little demonstrable effect on fishing locations, and the small effect that can be detected indicates that vessels move *towards* areas of RTCs (over a time-scale of months).

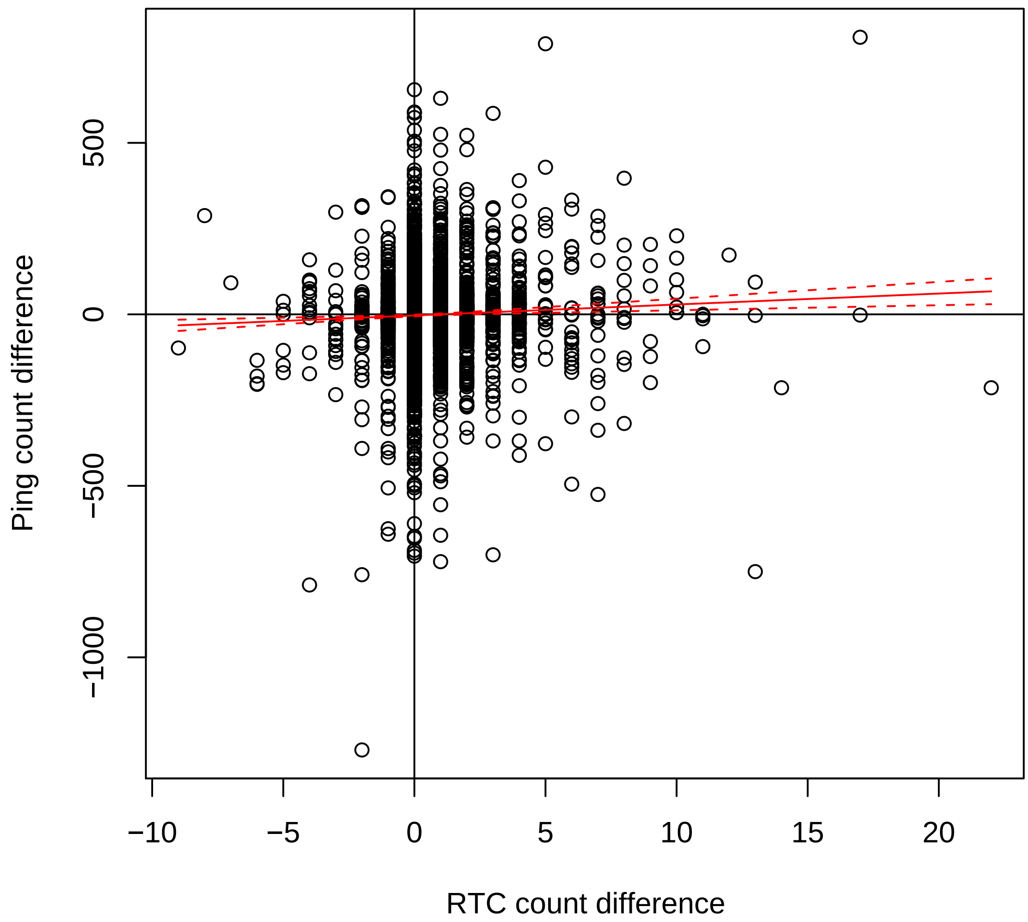


Figure 14.26: Regression analyses comparing ping count difference $d^{v}_{i,j,q,yc}$ and RTC count difference $d^{r}_{i,j,q,yc}$ for both inter-year comparisons, all quarters and all vessels. Only those comparisons with significantly different fishing distributions by the AD test have been included. Red lines give a fitted linear model (solid) with 95% confidence intervals (dashed).

Applying the contingency-table methodology described above to the new dataset produces the following.

$$T_{\text{all}} = \begin{array}{c} \\ d^r < 0 \\ d^r = 0 \\ d^r > 0 \end{array} \begin{bmatrix} d^v < 0 & d^v = 0 & d^v > 0 \\ 180 & 53 & 147 \\ 1690 & 1062 & 1681 \\ 560 & 215 & 592 \end{bmatrix} \qquad \begin{array}{l} \chi^2 = 60.247 \\ (\text{df} = 4, p < 1.0e-10) \end{array}$$

This indicates a strong contingency between d^r and d^v: that is, the variables are *not* independent, implying that changes in the RTC count do have a significant effect on changes in VMS ping counts. Furthermore, the direction of change is positive, as suggested by the weak relationship in Figure 14.26. To demonstrate this, I consider a version of T_{all} in which I have expressed each value as a percentage of the sum of the values *in that row*:

$$T^*_{\text{all}} = \begin{array}{c} \\ d^r < 0 \\ d^r = 0 \\ d^r > 0 \end{array} \begin{bmatrix} d^v < 0 & d^v = 0 & d^v > 0 \\ 47.4\% & 14.0\% & 38.7\% \\ 38.1\% & 24.0\% & 37.9\% \\ 41.0\% & 15.7\% & 43.3\% \end{bmatrix}$$

The percentage of comparisons for which $d^v < 0$ falls from 47.4% to 41.0% as d^r changes from negative to positive. At the same time, the percentage for which $d^v > 0$ increases from 38.7% to 43.3%. In other words: a positive change in VMS pings is linked to a positive change in RTCs, and a negative change in VMS pings is linked to a negative change in RTCs. The conclusion from both regression and contingency-table analysis is that, across the fleet as a whole (and only considering instances of significant changes in fishing location), vessels increase their fishing activity in areas over time which have increasing numbers of RTCs.

15 Conclusions

In this Chapter, I have applied two different approaches to the problem of characterising movement, both using VMS data from Scottish commercial fishing vessels, with the dual aims of (firstly) showing whether real-time closures (RTCs) are an effective management tool for North Sea cod, and (secondly) providing a characteristic case-study of fleet dynamics which a good fisheries simulation model would need to be able to replicate. The first approach considered only those vessels directly (in a specified sense) affected by real-time closures (RTCs), and used a spatio-temporal relative fish importance index (RFII) for cod to determine on a trip-by-trip basis whether vessels moved towards or away from areas of high cod abundance following the closure or reopening of an area. The second approach used cluster analysis to characterise the fishing areas used by a vessel, then compared changes in frequency of fishing in these areas with changes in the density of RTCs in the same areas to determine whether vessels moved towards or away from RTCs over a period of several years. These are relatively simple methods when compared with (for example) the trajectory-entropy modelling approach employed by Song et al. (2010) to model human movements using mobile-phone records, or the sophisticated foraging framework applied by Boyer and Walsh (2010) to individual position data for animals, but it could be argued that their very simplicity leads to greater understanding and interpretability of the outcomes (Harte 1988, Paola 2011).

At first sight, the results in this Chapter appear to be rather counter-intuitive. RTCs were set up by the Scottish Government with the express intention of encouraging vessels to move away from areas of high cod abundance, and thereby reduce cod mortality. The trip-specific analyses of vessels directly affected by RTCs (Section 13.2) showed that vessels will move away from RTCs while they are in operation, but are equally as likely to move back to the area occupied by an RTC once it reopens. The analysis of changes in fishing locations by quarter, and the relationship between those and changes in the number of RTCs in vessel-specific fishing areas (Section 14.5), concluded that across the entire fleet, an increase in imposed RTCs is linked to an increase in fishing effort (as measured by VMS pings). The conclusion from both analyses is that RTCs induce changes in fishing patterns only in the very short term, and in the long term may actually lead to the opposite response to that intended with increased fishing in areas with more RTCs.

On further reflection, however, this result is not very counter-intuitive at all. RTCs are placed where there are aggregations of cod and other profitable species. If they were in place for a long time then they might cause vessels to move elsewhere permanently, but as currently implemented they are of such short duration that they appear to serve principally as flags marking good areas to fish. There is no evidence in the available Scottish data from 2008-2010 that suggests that all vessels have intentionally avoided such areas: some have, but across the fleet as a whole the pattern is one of moving towards RTCs. During these years, the international fishing mortality on cod as estimated by ICES (ICES 2011c) has reduced, but not by as much as anticipated and by very much less than the mortality on other related species such as haddock, whiting and plaice.

The implications for fisheries managers are serious, as the analyses indicate that RTCs are not leading to the long-term changes in fishing locations that are required to reduce cod mortality. There are also important implications for the development of spatio-temporal fishery simulation models, which is the focus of this thesis. Section 14.3 showed that vessels are more likely to change fishing patterns in the second half of the year. Therefore, a useful fishery simulation model needs to be able to track quota availability for vessels, and include mechanisms for vessels to try and avoid fish for which they have little or no quota left. The conclusion given above suggests that such a model needs to be able simulate vessels moving towards short-term closed areas if these are imposed. This could be done by building in such a tendency and checking whether the fishing patterns thus generated reflect historical data, or by determining whether such movements arise as an emergent property of the model. In either case, a simulation model which could not replicate fleet responses of this kind could not be considered to be a very reliable tool for generating spatially-based fisheries management advice.

Chapter IV

A general simulation model

16 Spatio-temporal fishery simulation models

In this thesis, I have presented case studies of existing fishery management simulation models that have been used (and are still being used) as the basis for management advice and decisions (Chapter II). I have shown that these models use strong assumptions, often necessarily so given the available data and limited models of fleet dynamics: and how these assumptions can lead to problems which impinge on the utility of the models. I have given examples of management systems which could have great potential for helping to manage sustainable fisheries (see Chapters II), and I have presented analyses of new kinds of data (see Chapter III) that are becoming available and which could in theory be used in the service of said management systems.

What is not yet widely available, however, is a management simulation framework that can join these threads together. By this, I mean a model system which can incorporate the new forms of data on fishing times and locations, and other aspects of fleet dynamics, and which can be used to overcome the difficulties inherent in the extant management evaluation frameworks by allowing for changes in spatio-temporal patterns of fishing in response to management measures and environmental changes. Skagen (2004) pointed out that the type of management that is possible, and which would need to be evaluated in a quantitative sense, is dependent on the data that are available. As new types of data enter the scientific domain, new models are required to faciliate their analysis. It is also important that models are able to generate emergent and realistic economic activity: as highlighted by Lunn (2008), people (including fishermen) do not always behave as the rational, independent agents assumed by authors of neoclassical economic theory such as Clark (1976). The aim of this thesis is to develop and present some key components of such a modelling framework. The full framework is beyond the scope of the thesis, but work on it will continue once the thesis is completed and it is my intention that the framework will be ready for its intended use in the near future.

Several previous authors have explored these aspects: direct simulation examples include Bell et al. (2007) (SpatMan), Prince et al. (2008) and Bastardie et al. (2010), while the *ecoOcean* gaming simulation approach being developed by Nissen et al. (2011) will be applied to management evaluation in the near future (see also Briand and Giuliano 2011). I have built upon these ideas and started the development of a new implementation which more easily allows for the incorporation of fleet dynamics in terms of fishing activity choice, and I will describe this model for the remainder of this Chapter.

17 Representing space

Commercial fishing is an activity that takes place in space as well as in time. Fish stocks are not evenly distributed through the sea, and the decision about where to fish during a trip is just as important (if not more so) than decisions about when to fish, with what gear and for what species. Managers are also keenly aware of the importance of spatial fisheries policy, and closed (or otherwise limited) fishing areas are a key part of the available toolbox for managing fisheries. While not essential for developing policy (as I have shown in Chapter II), an evaluation framework with the ability to model space as well as time is likely to be more flexible and offer a wider scope for answering policy questions. Given this, I turn to the problem of how to represent space in a fisheries simulation model.

The model described in this thesis concurs with Nissen et al. (2011) in using a system of hexagons to partition the available space. Many previous authors (for example, Bell et al. 2007, Bastardie et al. 2010) have used squares instead. Squares have the advantage of simplifying cell referencing (in that the row-column identities of neighbouring cells are easy to specify, which is not the case with a hexagonal system as I shall show). However, the distances between the centroids of neighbouring squares are not constant. If centroids within row or column neighbours are one unit apart, a vessel moving one cell in a diagonal direction must travel $\sqrt{2}$ units. While this is not very difficult to code in (for example) shortest-distance algorithms, it is an unnecessary complication that can be avoided by using a hexagonal system in which movement distance between cell centroids is the same not matter which direction is taken. The other reasons for this choice are that I feel it leads to area representations that look more organic and realistic, and hexes are widely used in gaming and other simulations from which this model takes much inspiration.

17.1 A single hex

I consider first the representation of a single hexagon in Figure 17.1, with the centre at (x_c, y_c), six vertices numbered clockwise from (x_1, y_1) in the bottom left-hand corner, and six equal sides of length s. The internal spokes also have length s, and all of the internal angles are $\frac{\pi}{3}$ radians. If

$$x' = s\cos\frac{\pi}{3} = \frac{s}{2}, \tag{17.1}$$

$$y' = s\sin\frac{\pi}{3}, \tag{17.2}$$

then

$$x_c = x_1 + x', \tag{17.3}$$
$$y_c = y_1 + y'. \tag{17.4}$$

The remaining vertices are given by:

$$\begin{aligned}
(x_2, y_2) &= \left(x_1 - x', y_1 + y'\right) \\
(x_3, y_3) &= \left(x_1, y_1 + 2y'\right) \\
(x_4, y_4) &= \left(x_1 + s, y_1 + 2y'\right) \\
(x_5, y_5) &= \left(x_1 + s + x', y_1 + y'\right) \\
(x_6, y_6) &= \left(x_1 + s, y_1\right)
\end{aligned}$$

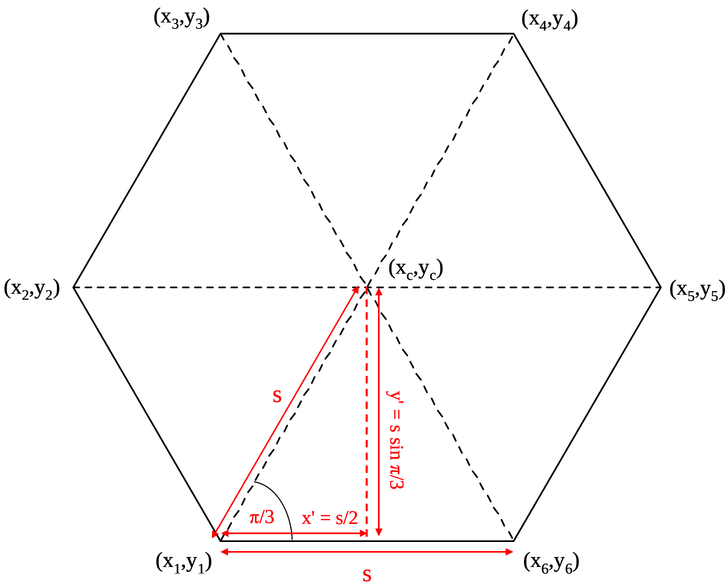


Figure 17.1: Geometry of a single hex for the simulation map.

17.2 MULTIPLE HEXES

The positions of hexes in rows and columns for the map are determined as follows. Suppose that the map is bounded in the x and y dimensions by $x \in [0, x_{\max}]$ and $y \in [0, y_{\max}]$, and that there should be n hexes in each row and column. Figure 17.2 gives a sample layout for $n = 5$, in which the hexes that form alternate rows are highlighted. Note that hex rows are necessarily crooked, while hex columns are straight.

I denote the bottom left-hand vertex of the hex in the ith column and the jth row by $(x_1, y_1)_{i,j}$. Considering the hex $(x_1, y_1)_{1,1}$ in the first row and first column, I can write

$$\begin{aligned} (x_1)_{1,1} &= s\cos\frac{\pi}{3} = \frac{s}{2}, && (17.5)\\ (y_1)_{1,1} &= s. && (17.6)\end{aligned}$$

Note firstly that these x-coordinate values will be the same for every hex in a column, since these are stacked vertically, so this can be generalised to

$$(x_1)_{1,j} = \frac{s}{2}. \tag{17.7}$$

Then, from Figure 17.2, the equivalent x-coordinates for the hexes in each row are given by:

$$\begin{aligned} (x_1)_{1,j} &= \frac{s}{2} && (17.8)\\ (x_1)_{2,j} &= (x_1)_{1,j} + s + \frac{s}{2} = \frac{4}{2}s && (17.9)\\ (x_1)_{3,j} &= (x_1)_{2,j} + s + \frac{s}{2} = \frac{7}{2}s && (17.10)\\ (x_1)_{4,j} &= (x_1)_{3,j} + s + \frac{s}{2} = \frac{10}{2}s && (17.11)\\ (x_1)_{5,j} &= (x_1)_{4,j} + s + \frac{s}{2} = \frac{13}{2}s && (17.12)\end{aligned}$$

And generally that:

$$(x_1)_{i,j} = \frac{s}{2} + (i-1)\frac{3}{2}s. \tag{17.13}$$

The y-coordinates of the bottom left-hand hex vertices depend on whether an even- or odd-numbered column is being referred to. For an odd-numbered column ($i \bmod 2 = 1$), such as the first column, the y-coordinates proceed upwards from the first row as follows:

$$\begin{aligned} (y_1)_{i,1} &= s && (17.14)\\ (y_1)_{i,2} &= (y_1)_{i,1} + 2s\sin\frac{\pi}{3} = s\left(1 + 2\sin\frac{\pi}{3}\right) && (17.15)\\ (y_1)_{i,3} &= (y_1)_{i,2} + 2s\sin\frac{\pi}{3} = s\left(1 + 4\sin\frac{\pi}{3}\right) && (17.16)\\ (y_1)_{i,4} &= (y_1)_{i,3} + 2s\sin\frac{\pi}{3} = s\left(1 + 6\sin\frac{\pi}{3}\right) && (17.17)\\ (y_1)_{i,5} &= (y_1)_{i,4} + 2s\sin\frac{\pi}{3} = s\left(1 + 8\sin\frac{\pi}{3}\right) && (17.18)\end{aligned}$$

And generally that:

$$(y_1)_{i,j}|_{i\text{ odd}} = s\left(1+2(i-1)\sin\frac{\pi}{3}\right). \tag{17.19}$$

For even-numbered columns (so that $i \bmod 2 = 0$), these y-coordinates are shifted downwards by $s\sin\frac{\pi}{3}$ (see Figure 17.2), so that Equation 17.19 becomes

$$(y_1)_{i,j}|_{i\text{ even}} = s\left(1+(2i-3)\sin\frac{\pi}{3}\right). \tag{17.20}$$

The maximum extent of the map in the x-direction can be obtained by calculating the x-coordinate of lower left-hand vertex of the nth hex on any given row (from Equation 17.13), and adding $\frac{3}{2}s$:

$$\begin{aligned} x_{\max} &= (x_1)_{n,j} + \frac{3}{2}s \\ &= \frac{s}{2} + (n-1)\frac{3}{2}s + \frac{3}{2}s \\ &= \frac{1}{2}s\,(3n+1) \end{aligned} \tag{17.21}$$

Similarly, using Equation 17.19:

$$\begin{aligned} y_{\max} &= (y_1)_{i,n}|_{i\text{ odd}} + 2s\sin\frac{\pi}{3} \\ &= s\left(1+2(n-1)\sin\frac{\pi}{3}\right) + 2s\sin\frac{\pi}{3} \\ &= s\left(1+2n\sin\frac{\pi}{3}\right) \end{aligned} \tag{17.22}$$

If the map is defined on the basis of $x_{\max}$ and the number of hexes to a side (n), then the length of a hex side s can be obtained from Equation 17.21 as

$$s = \frac{2x_{\max}}{3n+1}. \tag{17.23}$$

17.3 MOVING BETWEEN HEXES

Hexes have been used for map generation in this thesis for three main reasons: the distance required to move between adjacent locations is direction-invariant, which is not the case for a square grid; generated land areas look rather more realistic on a hex map; and hexes are widely used in gaming and other computer simulations from which the model presented here takes much inspiration (Stout 1996, Woodcock 2008). The main drawback to using hexes is that the indexing of locations when moving from one hex to an adjacent hex is not consistent, but depends on whether the start point is in an even-numbered or an odd-numbered hex column.

To illustrate this, consider Figure 17.3. This shows two particular hexes from Figure 17.2, one from an even column and one from an odd, along with the six neighbouring hexes in each case. Figure 17.3 gives the (i, j)-indices for all hexes, and the changes in i and j that would be generated by moving out of the central hex. These changes (or movement schedules) depend on the column in which the start hex is located. Moving in the "upwards-right" direction from a hex in an even-numbered column produces the index mapping $(i, j) \mapsto (i+1, j)$, for example, while the same movement from an odd-numbered column produces the mapping $(i, j) \mapsto (i+1, j+1)$.

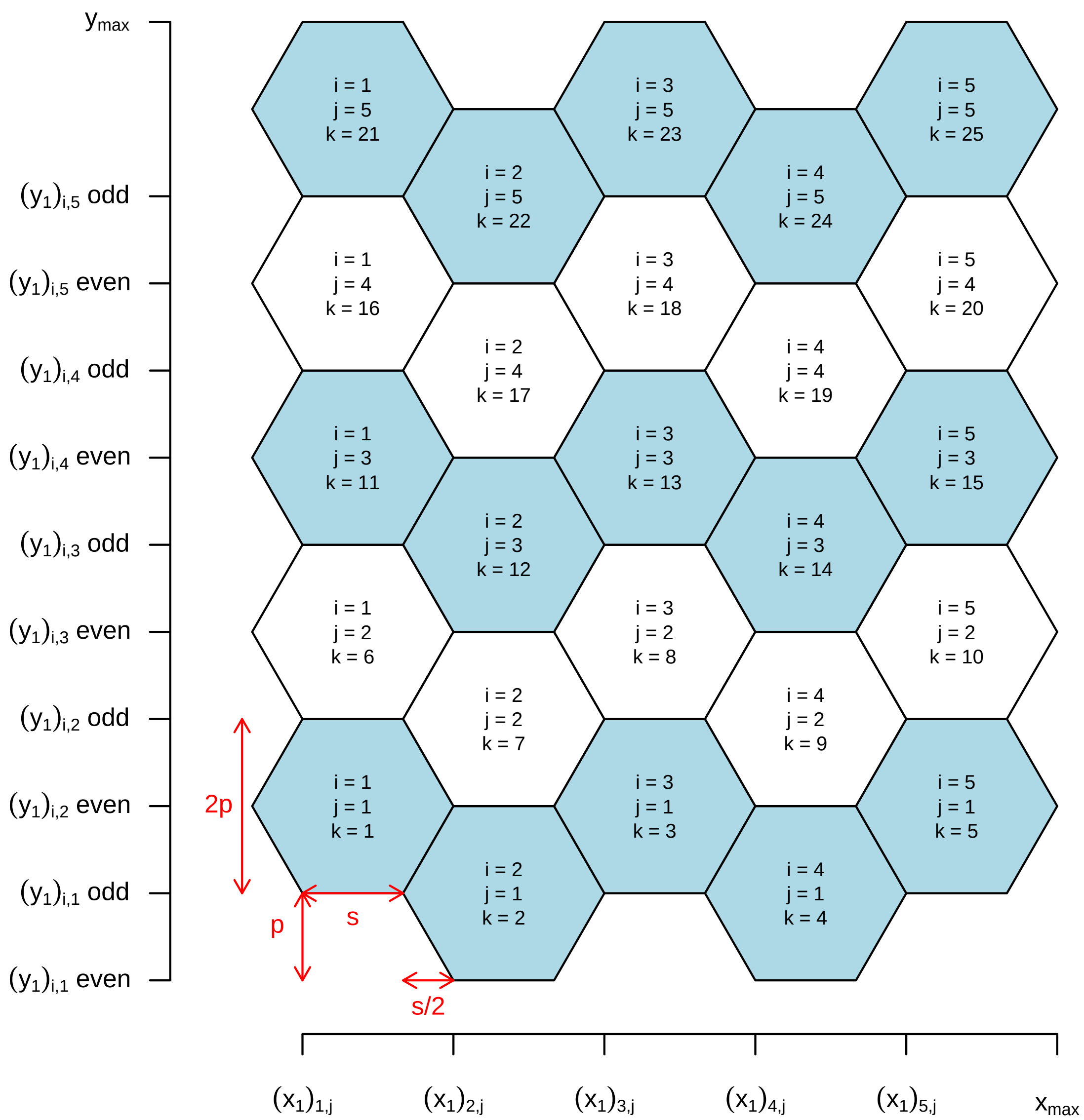


Figure 17.2: Geometry of a hex row for the simulation map (here $n = 5$). Alternate rows have been coloured differently for clarity. x and y coordinates for the bottom left-hand vertex of each hex are indicated, along with the maximum $x_{\max}$ and $y_{\max}$ values. Each hex is marked with row number (j), column number (i) and hex number (k). Key lengths are also highlighted: for brevity, I denote $p = s\sin\frac{\pi}{3}$.

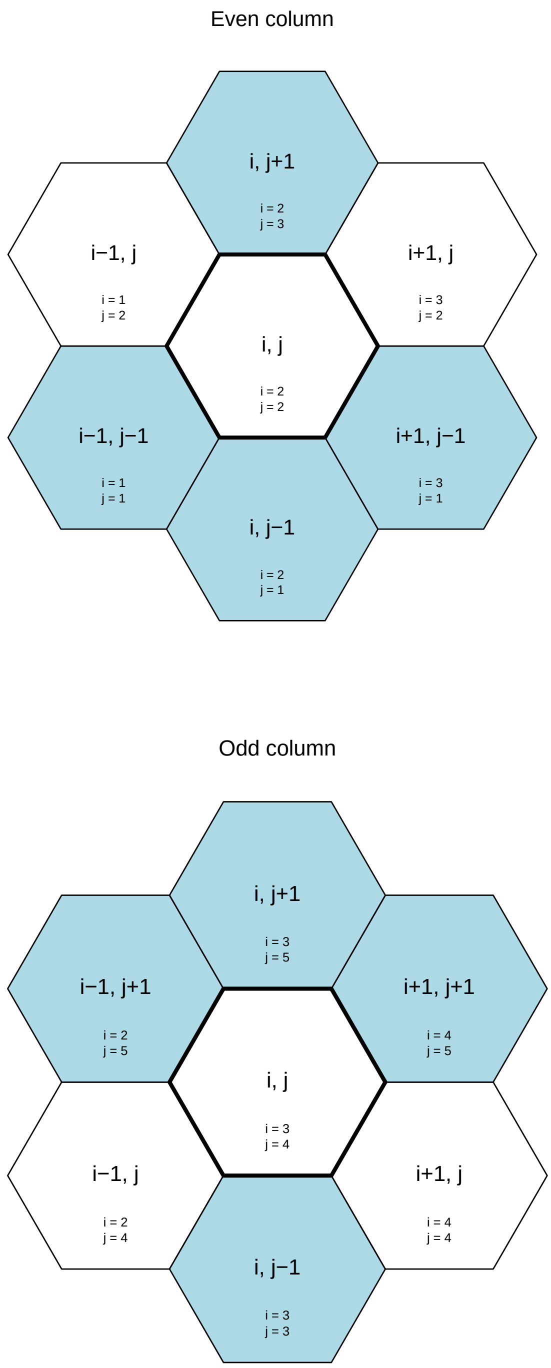


Figure 17.3: Movement schedules from hexes in even (upper) and odd (lower) hex columns. In both cases, the hexes displayed are a subset of those presented in Figure 17.2, and the same cell indexing (small numbers) and colouring scheme has been used here. The central hex is highlighted with a thicker boundary, while the larger-font captions in each of the surrounding hexes gives the change in the (i, j)-index that will be produced by moving from the central hex.

18 Generating a simulated area

Once a method of defining and specifying hexes had been established, the next step in generating a fisheries simulation was to develop code that stochastically generates a land- and sea-scape for the simulation to take place in. It would be possible to set up simulations using real coastlines and bathymetry, and indeed that needs to be done for application to policy advice, but for more general methodological work a large number of randomised areas were required to ensure that the subsequent applicability of the models is not limited to one or two types of locale. The challenge was then to set up the stochastic generation in such a way that the resultant area retains the salient features of real-world areas, and (equally importantly for simulations that are intended to inform policy managers) “looks right”: a simulation based on an area which looks unrealistic or physically impossible is likely to be treated with scepticism.

The steps involved in generating a suitable map were as follows. I defined five $n_h \times n_h$ boolean arrays, one for each of five possible depth categories (deep, medium, shallow, coast and inland), and denoted these respectively as $\mathbf{IJ}_{\text{dp}}$, $\mathbf{IJ}_{\text{md}}$, $\mathbf{IJ}_{\text{sh}}$, $\mathbf{IJ}_{\text{co}}$ and $\mathbf{IJ}_{\text{in}}$. All elements of these arrays were initially set to `false`. In order to plot the generated map, the boolean arrays were converted to depth records for each hex (i, j) according to the following pseudo-code decision tree (where depths are in metres):

```
if (IJ_dp[i,j])
    depth(i,j) = -200
else if (IJ_md[i,j])
    depth(i,j) = -100
else if (IJ_sh[i,j])
    depth(i,j) = -50
else if (IJ_co[i,j])
    depth(i,j) = 0
else if (IJ_in[i,j])
    depth(i,j) = 10
```

In step 1 of the process, all hex depths are initially set to -200 m, so $\mathbf{IJ}_{\text{dp}}(i, j) = \texttt{true}$ for all (i, j).

The next step is to generate medium-depth water hexes on top of the deep water hexes. I defined the proportion of deep water hexes that would be raised to medium-depth water hexes,

$$\rho_{\text{md}} = 0.75. \tag{18.1}$$

The number of medium-depth water hexes was then given by

$$n_{\text{md}} = \lfloor n_h^2 \rho_{\text{md}} + 0.5 \rfloor, \tag{18.2}$$

which is the number of hexes multiplied by the medium-depth proportion, rounded to the nearest integer. The positions of the n_{md} medium-depth water hexes were then determined by a random walk. The first such hex (i_0, j_0) was determined using

$$\begin{aligned} i_0 &\in \lfloor \mathrm{U}(2, n_h - 1) + 0.5 \rfloor, && (18.3) \\ j_0 &\in \lfloor \mathrm{U}(2, n_h - 1) + 0.5 \rfloor : && (18.4) \end{aligned}$$

that is, a randomly-determined deep-water hex not on the boundary of the map. $\mathbf{IJ}_{\text{md}}(i_0, j_0)$ was set to `true`, and $\mathbf{IJ}_{\text{dp}}(i_0, j_0)$ to `false`. Then the remaining medium-depth water hexes were generated using R code based on the following:

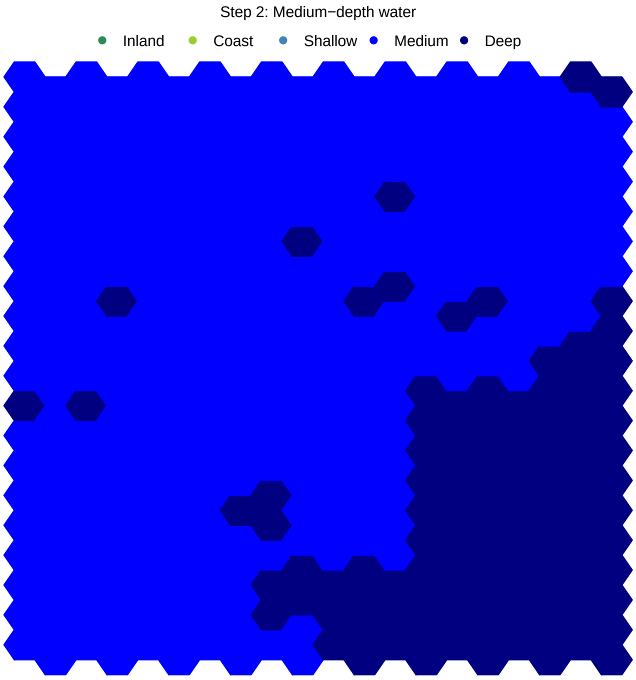
```
k = 2
while (k ≤ nh_md)
    in.area = false
    while (!in.area)
        hex.rnd = round(runif(1, min = 0.5, max = 6.5))
        if (x.rnd mod 2 = 0)
            x.test = x.rnd + hex.move.even$x[hex.rnd]
            y.test = y.rnd + hex.move.even$y[hex.rnd]
        else
            x.test = x.rnd + hex.move.odd$x[hex.rnd]
            y.test = y.rnd + hex.move.odd$y[hex.rnd]
        if (x.test in 1:nh & y.test in 1:nh)
            in.area = true
    if (!ij_md[x.test, y.test])
        ij_md[x.test, y.test] = true
        ij_dp[x.test, y.test] = false
        k = k + 1
```

At each hex (i, j), a random number between 1 and 6 is generated. This determines (following the scheme shown in Figure 17.3) the direction for the next step in the random walk. If this next hex (i^*, j^*) lies outside the area of the map defined by $(1:n_h, 1:n_h)$, then the boolean flag `in.area` remains `false` and a new direction is determined. Otherwise, $\mathbf{IJ}_{\text{md}}(i^*, j^*)$ is set to `true`, $\mathbf{IJ}_{\text{dp}}(i^*, j^*)$ is set to `false`, and the walk continues from (i^*, j^*) onwards. This process is repeated until n_{md} hexes have been converted to medium-depth water hexes. The results for the example map are given in Figure 18.1 (upper plot).

Following some experimentation with this approach, I noted that there was a tendency for the random walk to generate isolated single hexes (of either deep or medium-depth water). While this is not an adverse result in terms of the use in simulations to which the map is to be put, I felt that the isolates reduced the coherence and believability of the maps. To address this, I added a sweep function which determines which hexes (if any) are deep water completely surrounded by medium-depth water (the reverse cannot arise from the random walk). The function then converts these hexes from deep to medium-depth water and thus removes the isolates. The results for the example map are given in Figure 18.1 (lower plot), in which it can be seen that the four isolated deep water hexes have been converted to medium-depth water hexes. Hexes on the boundary of the map are not included in this sweep step.

Step 4 is to build shallow water hexes onto medium-depth water hexes. This follows a similar random-walk algorithm to that for medium-depth hexes, except that shallow water cannot be built on top of deep water. Hence, in the process of generating the $n_{\text{sh}} = \lfloor n_h^2 \rho_{\text{sh}} + 0.5 \rfloor$ shallow water hexes (where $\rho_{\text{sh}} = 0.5$), the walk moves forward in the randomly-determined direction only if new hex is both within the area of the map, *and* is already defined as a medium-depth water hex. Changing from medium-depth water to shallow water for a given hex is implemented by altering the values of the relevant elements of $\mathbf{IJ}_{\text{md}}$ and $\mathbf{IJ}_{\text{sh}}$, as before, and I include a further sweep to remove isolates, also as before. The results for the example are given in Figure 18.2. Continuing upwards, I now modify a proportion of the shallow water hexes to make them land (using $\rho_{\text{in}} = 0.25$), adding a sweep to deal with single-hex lakes and land bridges (defined as any land hex that has two non-contiguous land hexes joined to it; Figure 18.3). I also note that land hexes cannot form part of the boundary of the map, as this can lead to large areas of sea being isolated from each other. The final steps are a last sweep for single hexes of any depth (Figure 18.4, upper plot) and a function to redefine those land hexes with adjoining sea hexes as "coast" hexes (Figure 18.4, lower plot). These have a special function in the simulation, as they are the only suitable locations for ports.

The maps generated by this process are randomly determined, but they are based on two main regular principles: depth determination proceeds from the bottom up, and an attempt is made to deal with isolated hexes. The intended proportion of hexes within each depth category is also maintained, for the most part, although minor deviations will occur as the results of isolate removal (Figure 18.5). The process is also completely scalable: Figure 18.6 shows two simulated maps with $n_h = 5$ and 100 respectively.



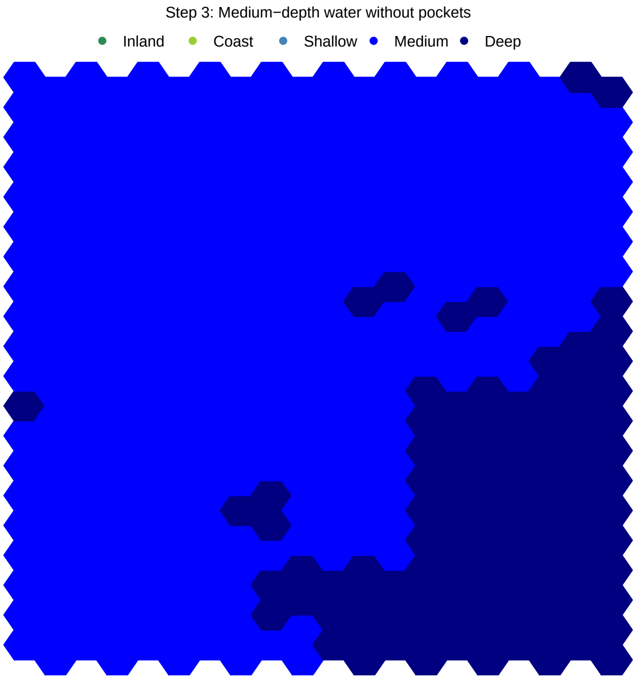
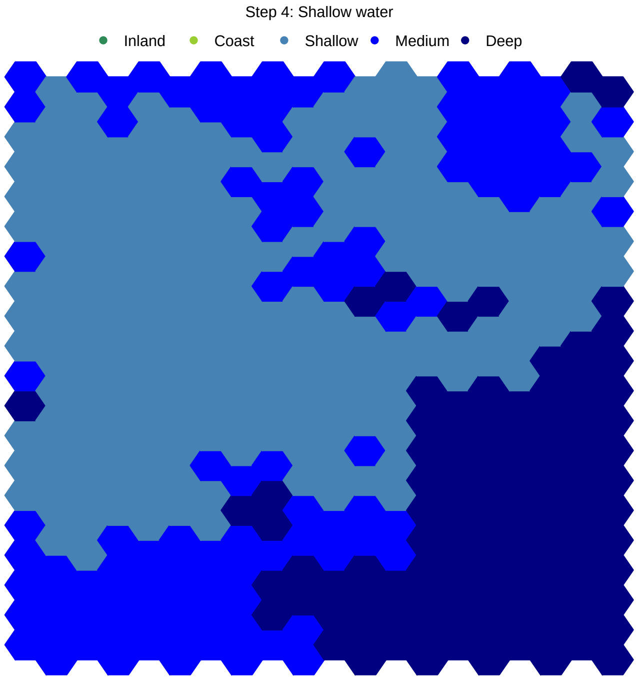


Figure 18.1: Hex map generation: steps 2 (medium-depth water) and 3 (removing isolated hexes from the medium-depth water array). Here the number of hexes to each side of the map $n_h = 20$. The legend gives the colours used to indicate each depth band.



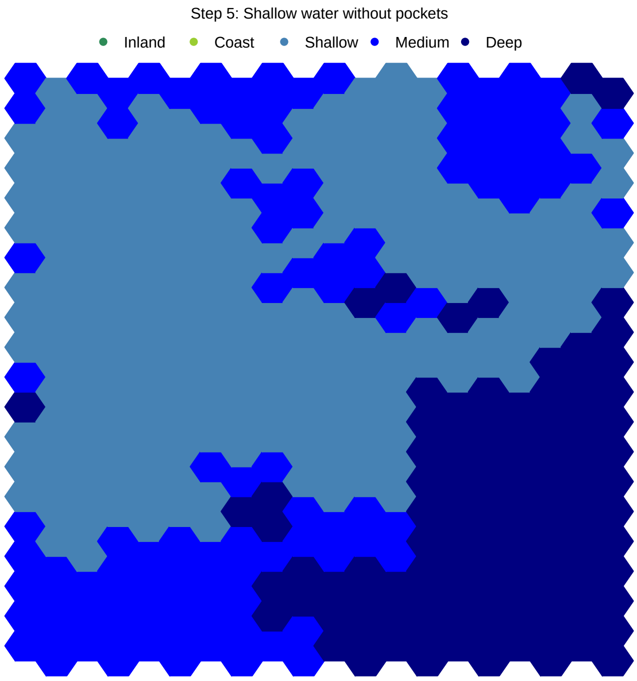


Figure 18.2: Hex map generation: steps 4 (shallow water) and 5 (removing isolated hexes from the shallow water array). Here the number of hexes to each side of the map $n_h = 20$. The legend gives the colours used to indicate each depth band.

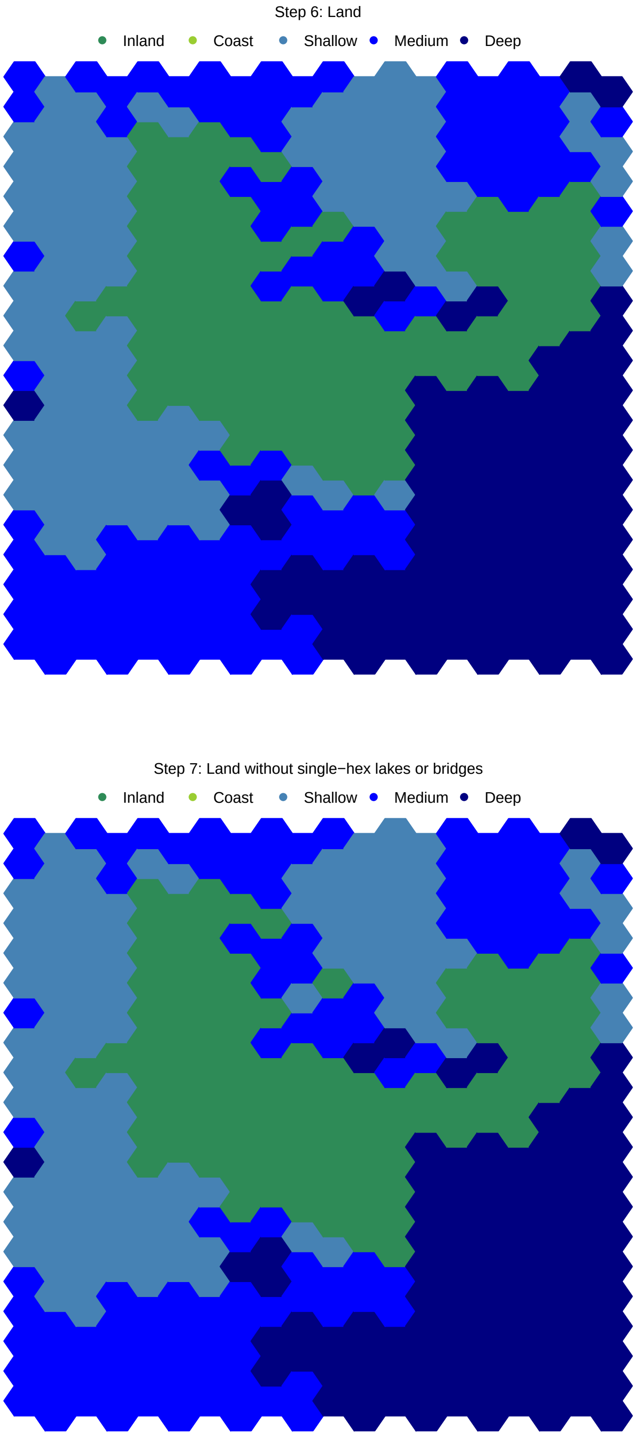


Figure 18.3: Hex map generation: steps 6 (land) and 7 (removal of single-hex lakes and land bridges). Here the number of hexes to each side of the map $n_h = 20$. The legend gives the colours used to indicate each depth band.

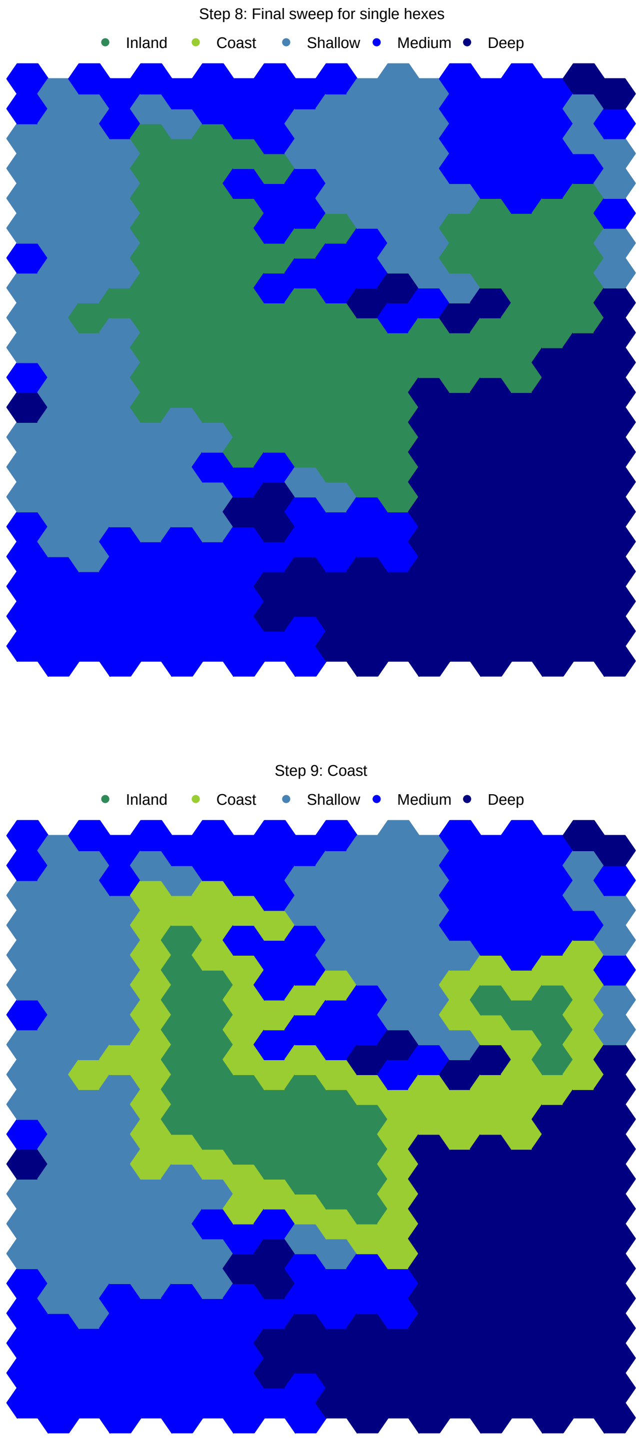


Figure 18.4: Hex map generation: steps 8 (final sweep to remove isolates) and 9 (definition of coastal hexes). Here the number of hexes to each side of the map $n_h = 20$. The legend gives the colours used to indicate each depth band.

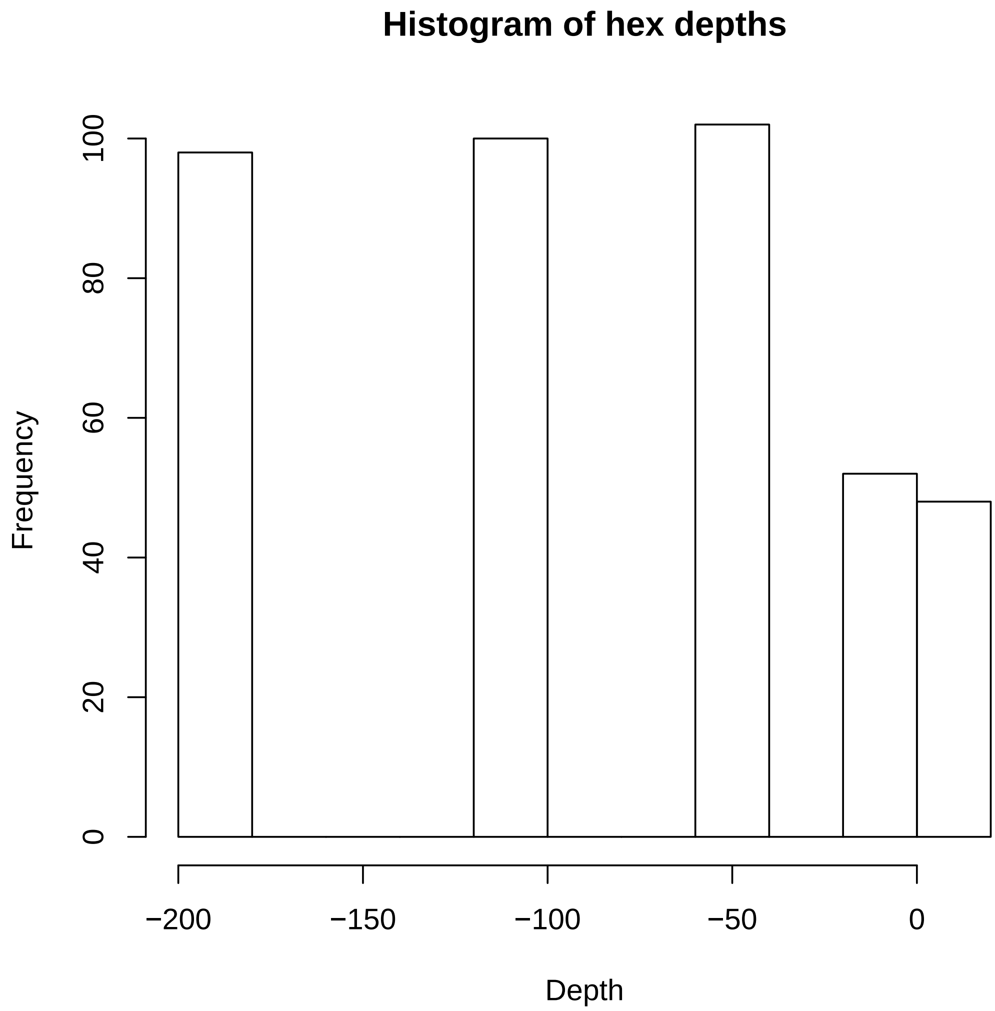


Figure 18.5: Hex map generation: resultant depth histogram, for example in which $n_h = 20$.

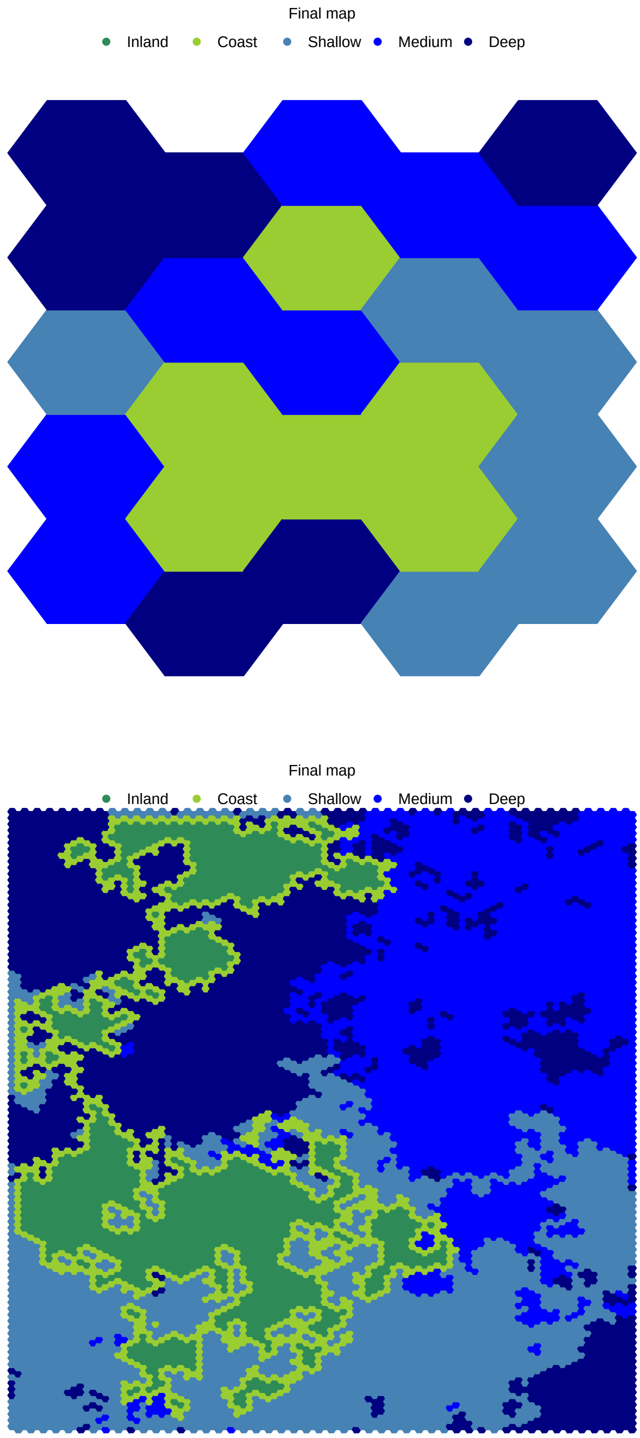


Figure 18.6: Hex map generation: examples for $n_h = 5$ (upper) and $n_h = 100$ (lower). The legend gives the colours used to indicate each depth band.

19 Path finding

Having generated stochastic simulation maps, the next requirement was for a method to determine the minimum distance from any given hex to any other hex, assuming that only sea hexes are passable. In order to minimise fuel use and other costs from being at sea, it is reasonable to assume that skippers will usually take the shortest route possible between their home harbour and their selected fishing grounds, or between one fishing ground and another, and to be realistic the simulation must reflect this.

Many different approaches to the problem of path determination exist, and determining the shortest possible distance between two points on a non-trivial map is a problem that occurs in many fields. Much of the extant literature refers to work done in the context of computer games (Woodcock 2008). An example is Stout (1996), which is very well-cited and has considerable status as the standard work on the subject of pathfinding (particularly in the context of gaming). Stout (1996) provides a downloadable program *PathDemo* which allows testing of many different types of pathfinding algorithm, and in the course of developing pathfinding approaches for the fisheries simulation I implemented several of these in R.

Many of the simple algorithms can work well, but run into difficulties when presented with situations to which they are not well suited. An example is given in Figure 19.1. Here I have implemented an algorithm which uses the following simple decision rule: "head towards the target, turn right or left if hitting land, choose shortest such path." The Figure demonstrates that such an approach can easily get stuck, and is clearly not a generally-applicable solution.

One of the most flexible and widely-used pathfinding algorithms is the so-called A* algorithm: an example using *PathDemo* is given in Figure 19.2. The A* algorithm was first described by Hart et al. (1968), in relation to theoretical graph analysis, with further developments following shortly thereafter (Hart et al. 1972). It is a recursive-tree algorithm that searches down potential path trees to determine the shortest suitable paths. It differs from a simple depth or breadth first search in that it uses a heuristic to direct the search in the direction of the target. In other words, each node (or hex) n is given a score $f(n)$, where

$$f(n) = \omega_g g(n) + \omega_h h(n). \tag{19.1}$$

Here $g(n)$ is the actual cost of moving from the start node to node n, in terms of distance travelled, while $h(n)$ is an estimate of the distance from node n to the target node. $h(n)$ is often chosen as the Euclidean (straight line) distance, but other formulations are possible. ω_g and ω_h are weightings terms. This approach generally improves the process in terms of finding the shortest path. Although there can be situations where it makes it slower, the heuristic can be tailored to the analysis. Too high a value of the heuristic weighting ω_h can lead to suboptimal paths: should this be a problem, the algorithm can be made to mimic a simple depth-first search by setting $\omega_h = 0$.

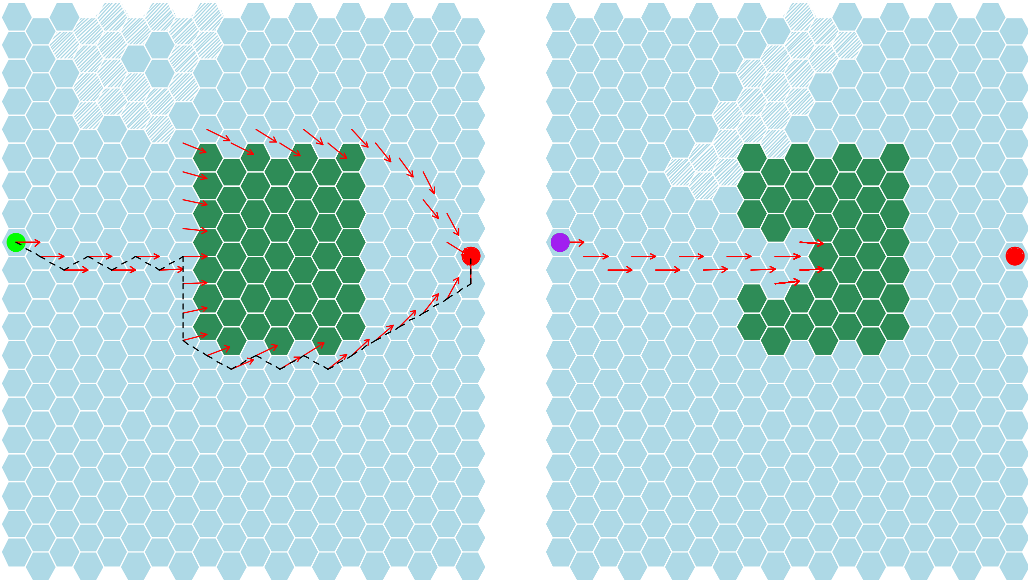


Figure 19.1: Path examples when using a simple "head towards the target, turn right or left if hitting land, choose shortest such path." Green and purple dots show start hexes, red dots are target hexes. Sea hexes are blue (or hatched blue if also spawning areas), land hexes are green. Red arrows show direction towards target from each test hex. Dotted black line in the left plot shows the selected shortest route. No shortest route can be found using this method for the right-hand map.

The properties of the A* algorithm, in particular its optimality, have been studied in considerable depth in the literature: in addition to Hart et al. (1968) and Hart et al. (1972), examples include Dechter and Pearl (1985). The pseudo-code given by Stout (1996) is as follows:

```
priorityqueue Open
list Closed
AStarSearch
    s.g = 0  // s is the start node
    s.h = GoalDistEstimate(s)
    s.f = s.g + s.h
    s.parent = null
    push s on Open
```

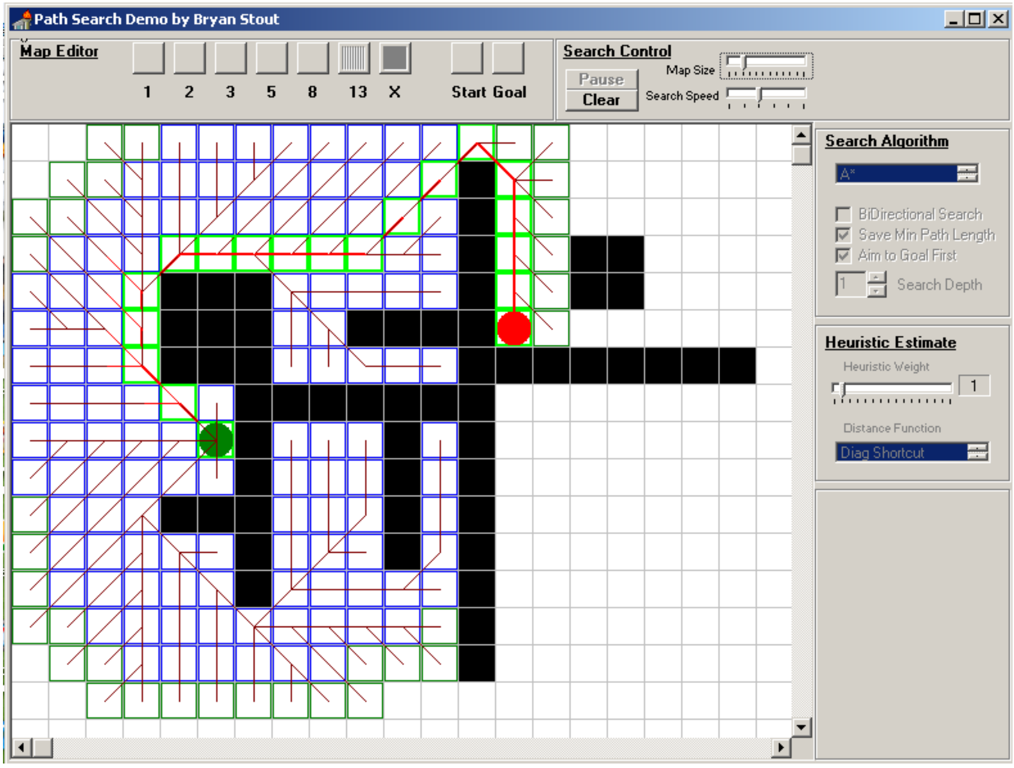


Figure 19.2: Example of the use of the A* algorithm in PathDemo (Stout 1996). The start and end points of the path are shown as green and red points respectively, impassable squares are given in black, and the shortest possible path is shown as a red line. The other lines show trial paths which were rejected.

```
while Open is not empty
    pop node n from Open   // n has the lowest f
if n is a goal node
    construct path
    return success
for each successor n' of n
    newg = n.g + cost(n,n')
    if n' is in Open or Closed,
         and n'.g < = newg
           skip
    n'.parent = n
    n'.g = newg
    n'.h = GoalDistEstimate(n')
    n'.f = n'.g + n'.h
    if n' is in Closed
```

```
        remove it from Closed
    if n' is not yet in Open
        push n' on Open
  push n onto Closed
  return failure // if no path found
```

I illustrate the A* algorithm through a simple example. Consider the generated area in Figure 19.3. This includes 25 hexes in a 5×5 grid, with six land hexes positioned centrally. The aim is to determine the shortest path from the Start hex (marked S) to the End hex (marked E). Listed on each hex are five numbers, namely (from top to bottom): the hex identifier i along with the identifier of the parent of the hex in the current best path, the "heuristic" value H (see below), the number of hexes G traversed to reach hex i from the Start hex, and the hex score $F = G + H$. In this case (and in the simulation implementation), the "heuristic" H is the straight line distance from the centre of hex i to the centre of the End hex (calculated using Pythagoras' Theorem), and H is given equal weight to G in the calculation of F.

The algorithm proceeds according to the following steps:

1. Add the Start hex to the Closed list.

2. Add the admissible (non-land) neighbours (hexes 8 and 9) of the Start hex to the Open list, noting the parent hex (S, in this case) and calculate their G, H and F scores. This is the point reached in Figure 19.3.

3. Pick the element of the Open list with the lowest F score (hex 8, in this case). Move this element to the Closed list. Add all admissible neighbours (non-land and not already in the Closed list) of this element to the Open list. If a neighbouring hex is already in the Open list, only replace it in this step if the new G score is lower than the existing G score. The result of these steps can be seen in Figure 19.4.

4. Repeat for the element of the new Open list with the lowest F score (hex 9), to produce the lists in Figure 19.5.

5. Continue until the End hex E appears in the Closed list (Figure 19.6).

Once this stage is reached, the required shortest path can be recovered by following the trail of Parent hexes in the Closed list. In this case, the hexes on the path (reading backwards from the End hex) are $(E, 16, 11, 6, 2, 8, S)$, and the path length is 6 hexes.

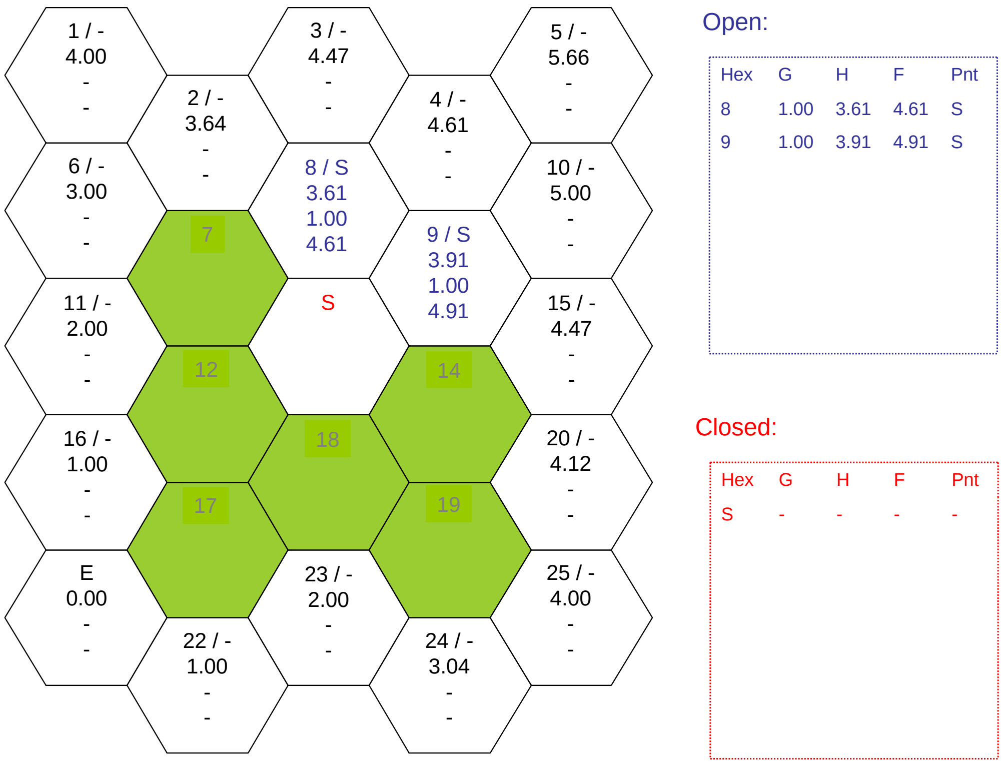
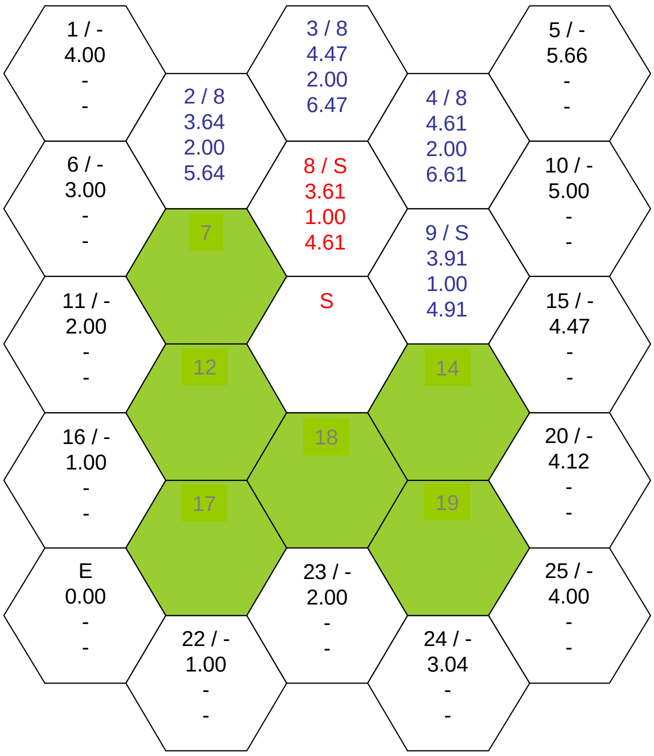


Figure 19.3: Step 1 of a simple demonstration of the A* algorithm. The Start hex is marked by S, the End hex by E, and all non-land hexes (apart from the Start hex S) are marked by the hex identifier i, the "heuristic" value H (see text), the number of hexes G traversed to reach hex i from the Start hex, and the hex score $F = G + H$ (in that order). A hyphen indicates that a value has not yet been determined. The tables list the Open and Closed hexes, along with the F, G and H scores and the current Parent of each hex.



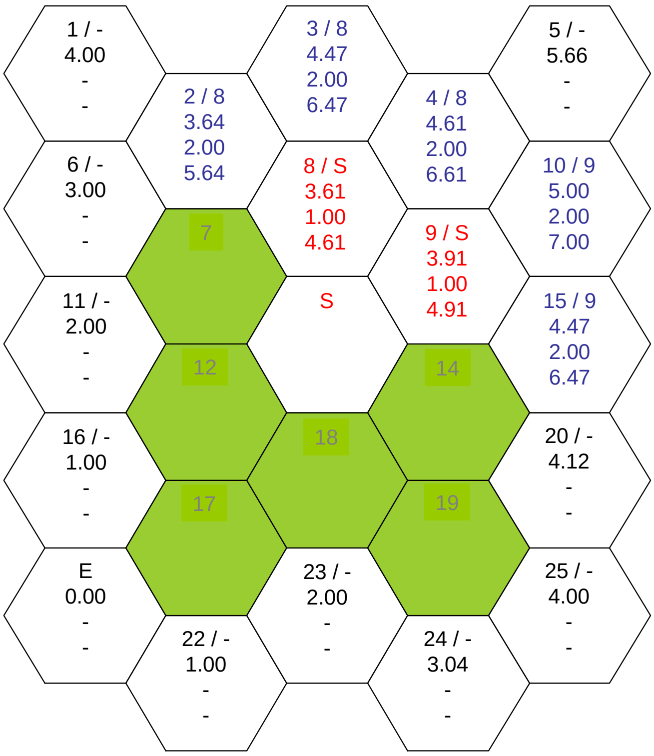
Open:

Hex	G	H	F	Pnt
9	1.00	3.91	4.91	S
2	2.00	3.64	5.64	8
3	2.00	4.47	6.47	8
4	2.00	4.61	6.61	8

Closed:

Hex	G	H	F	Pnt
S	-	-	-	-
8	1.00	3.61	4.61	S

Figure 19.4: Step 2 of a simple demonstration of the A* algorithm. See caption to Figure 19.3 for details.



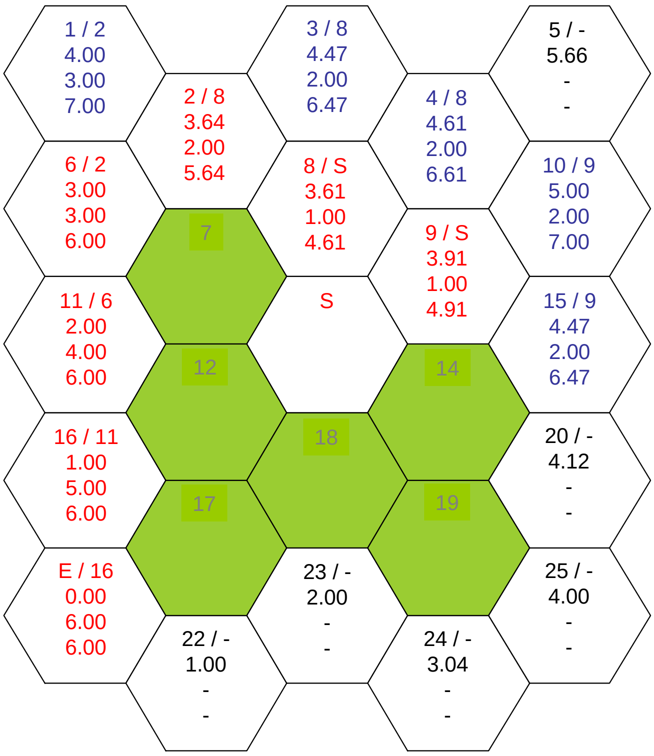
Open:

Hex	G	H	F	Pnt
2	2.00	3.64	5.64	8
3	2.00	4.47	6.47	8
4	2.00	4.61	6.61	8
10	2.00	5.00	7.00	9
15	2.00	4.47	6.47	9

Closed:

Hex	G	H	F	Pnt
S	-	-	-	-
8	1.00	3.61	4.61	S
9	1.00	3.91	4.91	S

Figure 19.5: Step 3 of a simple demonstration of the A* algorithm. See caption to Figure 19.3 for details.



Open:

Hex	G	H	F	Pnt
3	2.00	4.47	6.47	8
4	2.00	4.61	6.61	8
10	2.00	5.00	7.00	9
15	2.00	4.47	6.47	9
1	3.00	4.00	7.00	2

Closed:

Hex	G	H	F	Pnt
S	-	-	-	-
8	1.00	3.61	4.61	S
9	1.00	3.91	4.91	S
2	2.00	3.64	5.64	8
6	3.00	3.00	6.00	2
11	4.00	2.00	6.00	6
16	5.00	1.00	6.00	11
E	6.00	0.00	6.00	16

Figure 19.6: Step 4 of a simple demonstration of the A* algorithm. See caption to Figure 19.3 for details.

My implementation in R followed the standard A* algorithm quite faithfully, although with minor modifications to allow for the restrictions of the R language. Examples of the application of the algorithm to find the shortest path between points in two runs of my simulation model are given in Figure 19.7. The algorithm will always find the shortest path if a path exists, and if not, it will report that no such path is possible. The times taken to find the paths in Figure 19.7 are as follows: although the code is written entirely in native R code and should therefore be quite slow, the run times are not unreasonable.

n_h	Start point	Length of path (hexes)	Time taken for estimation (s)
20	1	4	0.10
20	2	25	1.14
20	3	26	1.33
100	1	68	8.25
100	2	103	22.20
100	3	55	7.24

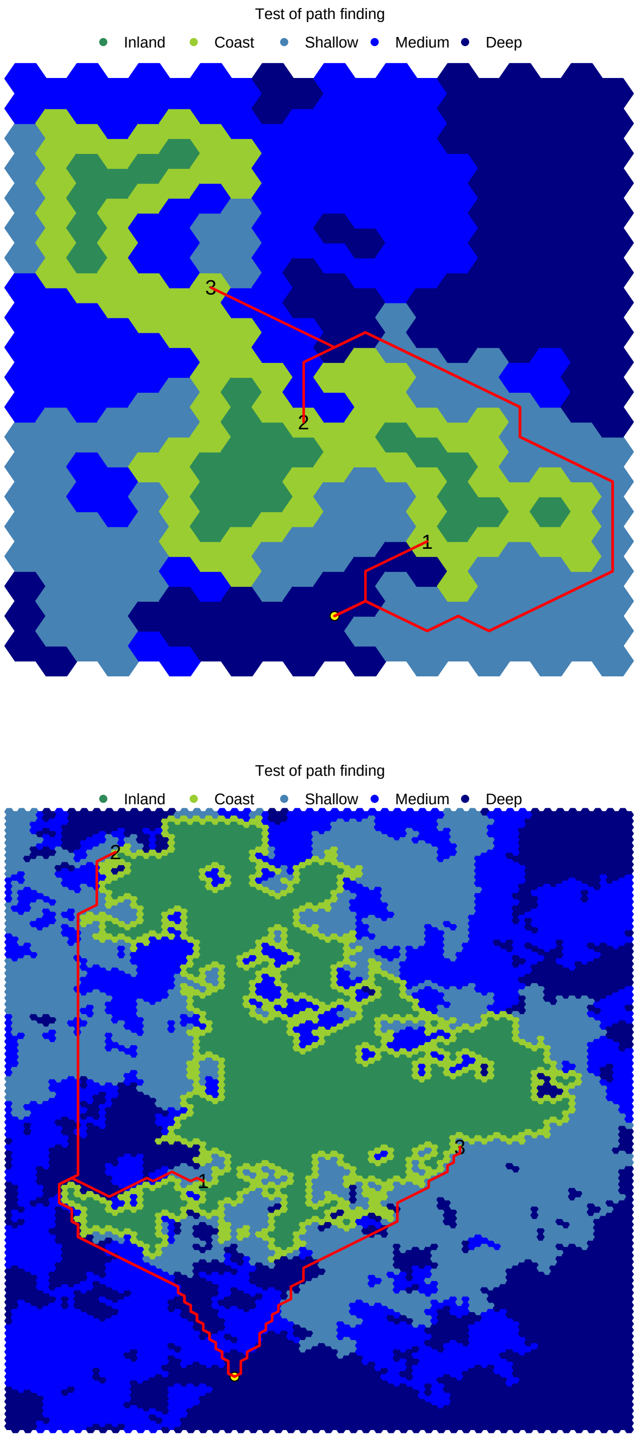


Figure 19.7: Path-finding using the A* algorithm: examples for $n_h = 20$ (upper) and $n_h = 100$ (lower). The legend gives the colours used to indicate each depth band. The yellow dot shows the centre of the target hex. Three coastal hexes are marked, and red lines show the shortest path from each to the target hex.

20 Representing fish populations and fishing vessels

Once the geography and bathymetry of the simulation area has been defined, the next step is to populate the area with fish. Fish population simulations have a long history, and there are many more extant models of fish than there are of fisheries (see Hart and Pitcher 1983, for a useful introduction). Given that the main foci of my simulation are the dynamics of fleets and the responses of fishermen to regulation changes, the model of fish populations on which subsequent models of fisheries will be built does not need to be very fully realised. As I discussed in Chapter I, fish population biology needs to be characterised in a fisheries model *only to the extent necessary* (Harte 1988, Paola 2011), although what that means is dependent on the context and it is also important to remember that: "there is a need for greater emphasis in simulation tests on the implications of alternative stock structures, spatial dynamics and ecosystem effects" (Butterworth 2008b, p. 385), to which I would add *fishery response patterns*.

The first (conceptual) version of the fish population model that I created for this purpose was based on individuals, following such authors as Hinckley et al. (1996) The second (actual) version was a rather complex, age- and length-structured stochastic model of stock distributions that allowed for variations in growth, and which enabled models of fishing gear (and other sources of mortality) to be fully length-specified. While this approach would have produced realistic models with many of the characteristics of actual fish stocks, there were two drawbacks. Firstly, it was very memory-intensive: using one-cm length classes, a model of a cod-like population would need perhaps 100 such classes for every hex. If ages are used, this requirement drops dramatically, to 10 or 15 age-class records per hex. Secondly, and more problematically, growth needs to be treated carefully for a length-based model to produce appropriate results. Gurney et al. (2007) show that a monotonic rescaling of length classes into variable-extent size classes prevents unwanted bunching effects for larger fish, but time did not permit this to be done for the analysis reported in this thesis. Most processes affecting marine fish are driven by length (or size) rather than by age, but for this version of the model I considered it sufficient to implement an age-based modelling approach only. The extension to a length-based approach must be reserved for future work.

The biological simulation was set up in the first instance (and without loss of generality) to model one fish stock, although as the approach uses a list in R it would be readily extendible to several stocks. The first stock was designed to mimic the biological characteristics of cod (*Gadus morhua*) in the North Sea (ICES Subarea IV and Divisions IIIaN and VIId; see Figure 4.1), due to its high profile in European fisheries management and its economic importance for many of the fleets that I intend for the model to simulate. Data on North Sea cod were taken from ICES (2011c) and used to generate appropriate models of biological parameters, as described below.

20.1 WEIGHTS AT AGE

Mean weights-at-age in the North Sea cod stock $W_{a,y}$ for ages 1-11+ and years 2001-2010 were extracted from ICES (2011c) and are reproduced in Table 20.1. Note that these are actually mean *catch* weights-at-age, but ICES (2011c) assumes that these are the same as *stock* weights-at-age and I make the same assumption here. Rough estimates for age 0 have been included here, as age-0 fish appear in my simulation but not in the ICES assessment. Only the most recent 10 years were used, as growth characterisics for fish such as cod can change considerably through time and more historical weight data may not be relevant (Baudron et al. 2011, Jaworski 2011). These data were used to estimate parameter values for the following parameterisation of the von Bertalanffy individual growth model

$$W_{a,y} = W_\infty \left(1 - \exp(-a\kappa_{\text{vb}})\right)^{\beta_{\text{vb}}} \tag{20.1}$$

which I obtain by substituting the usual allometric weight relationship $W_{a,y} = \alpha_{\text{vb}} L_{a,y}^{\beta_{\text{vb}}}$ into the classic von Bertalanffy model (von Bertalanffy 1934, Beverton and Holt 1957)

$$L_{a,y} = L_\infty \left(1 - \exp\left(-\kappa_{\text{vb}}\left(t - t_0\right)\right)\right), \tag{20.2}$$

setting $W_\infty = \alpha_{\text{vb}} L_\infty^{\beta_{\text{vb}}}$ and allowing $t_0 = 0$. Parameters were estimated by nonlinear least-squares regression using the `nls.lm` function in the R `minpack` library (Elzhov et al. 2010). The Hessian $\mathbf{H}$ of this model fit was then used to define a multivariate Normal distribution of the model parameters, and the R function `mvrnorm` (Venables and Ripley 2002, Ripley 2011) applied to draw 1000 samples from this distribution. This generated 1000 values of W_∞, κ_{vb} and β_{vb} in such a way that their variance-covariance structure from the Hessian was maintained. Each of these parameter resamples was then used in turn to produce a von Bertalanffy curve, and I derived a 95% confidence interval about the fitted von Bertalanffy curve from the 2.5% and 97.5% quantiles of these 1000 curves at each age (see Figure 20.1). This is analogous to the uncertainty estimation procedure using for the SURBA stock assessment model (see Section 8.3.3).

In the simulations, increases in weights-at-age were applied each week, following the smooth fitted von Bertalanffy curve in Figure 20.1.

Year	Age 0	1	2	3	4	5	6	7	8	9	10	11+
2001	0.10	0.37	0.61	2.09	3.66	5.87	7.33	9.26	10.08	12.06	12.01	10.20
2002	0.10	0.46	0.92	1.71	3.86	5.37	7.99	9.63	10.40	10.96	12.82	11.84
2003	0.10	0.28	0.75	1.53	3.19	5.11	7.27	8.63	12.06	12.85	10.77	17.35
2004	0.10	0.34	0.67	1.71	3.10	5.17	7.43	8.68	9.80	11.68	13.06	14.14
2005	0.10	0.35	0.90	1.95	3.70	5.06	7.56	9.61	11.23	11.50	13.33	15.34
2006	0.10	0.22	0.77	1.97	3.61	5.59	6.85	8.91	10.64	12.22	9.21	10.77
2007	0.10	0.28	0.86	2.19	4.06	5.61	8.47	8.92	9.90	12.36	13.73	8.15
2008	0.10	0.33	0.90	1.97	3.83	5.69	7.23	9.32	9.88	11.60	15.28	13.30
2009	0.10	0.39	1.03	2.34	3.97	6.04	7.54	8.80	10.21	10.00	11.92	13.60
2010	0.10	0.29	1.03	2.45	4.20	6.05	7.69	9.23	10.31	10.80	11.46	10.52

Table 20.1: Mean catch (stock) weights-at-age for North Sea cod. Source: ICES (2011c)

20.2 NATURAL MORTALITY

For a number of years, the ICES Working Group on Multispecies Assessment Methods (WGSAM: ICES 2008b, ICES 2009b, ICES 2010b) has produced estimates of natural mortality for the main stocks of interest in European waters. These are derived using a multispecies assessment model (SMS: Lewy and Vinther 2004), based on stomach-contents data in addition to the standard catch and survey data. The last large-scale survey of stomach contents was in 1991 (ICES 1996) so the predation links are necessarily out of date, but ICES recommend that the resultant estimates of natural mortality M are appropriate if used with care. The assessment of North Sea cod is carried out using these estimated, time-varying natural mortality rates (ICES 2011c), so it is reasonable for them to be used to characterise my simulation also.

Estimates of natural mortality M from ICES (2008b), *via* ICES (2011c), are given in Table 20.2. The North Sea cod assessment does not include age-0 fish, so the M estimates have been augmented with a fixed value of 1.5 for age 0: this seems a reasonable value with reference to other gadoid stocks in the North Sea (for example, $M_0 = 2.05$ for haddock; ICES 2011c). I fitted the following simple model to these data, by non-linear least-squares regression using the `nls.lm` function in the R `minpack` library (Elzhov et al. 2010):

$$M_a = b_m + \frac{a_m}{a+1}. \tag{20.3}$$

Using an approach analogous to that used for weights-at-age (Section 20.1), I also generated 95% confidence limits about the fitted curve. The data from ICES (2011c), along with the fitted line and its confidence bounds, are presented in Figure 20.2.

	Age							
Year	0	1	2	3	4	5	6	7+
2001	1.50	0.56	0.29	0.44	0.27	0.27	0.35	0.20
2002	1.50	0.53	0.28	0.43	0.27	0.27	0.35	0.20
2003	1.50	0.51	0.28	0.42	0.27	0.27	0.34	0.20
2004	1.50	0.50	0.27	0.41	0.27	0.27	0.34	0.20
2005	1.50	0.49	0.27	0.40	0.26	0.26	0.34	0.20
2006	1.50	0.47	0.27	0.39	0.26	0.26	0.33	0.20
2007	1.50	0.46	0.26	0.38	0.26	0.26	0.33	0.20
2008	1.50	0.46	0.26	0.38	0.26	0.26	0.33	0.20
2009	1.50	0.46	0.26	0.38	0.26	0.26	0.33	0.20
2010	1.50	0.46	0.26	0.38	0.26	0.26	0.33	0.20

Table 20.2: Natural mortality M estimates for North Sea cod. Sources: ICES (2008b), ICES (2011c).

20.3 MATURITY AT AGE

The ICES assessment of North Sea cod (ICES 2011c) makes the assumption that the proportion of fish that are mature at each age is fixed through time. Recent work that I undertook with the North Sea haddock stock (see ICES 2011a) would suggest that this is unlikely to be true for any gadoid stock, but in the absence of appropriate data it is difficult to produce improved models of changes in North Sea cod maturation. However, in the simulations it is important that increases in proportion mature at age $\text{Mat}_{a,y}$ are applied each week. To enable this, I fitted the following function to the data in Table 20.3,

$$\text{Mat}_{a,y} = \frac{e^{\alpha_{\text{mat}}+\beta_{\text{mat}}}}{1+e^{\alpha_{\text{mat}}+\beta_{\text{mat}}}}, \tag{20.4}$$

for which $\alpha_{\text{mat}} = -6.058$ and $\beta_{\text{mat}} = 1.623$, and the resultant curve (Figure 20.3) is applied to generate increases in maturity for every week in the simulation.

Age	0	1	2	3	4	5	6 and older
Proportion mature	0.00	0.01	0.05	0.23	0.62	0.86	1.00

Table 20.3: Proportion mature-at-age for North Sea cod. Source: ICES (2011c)

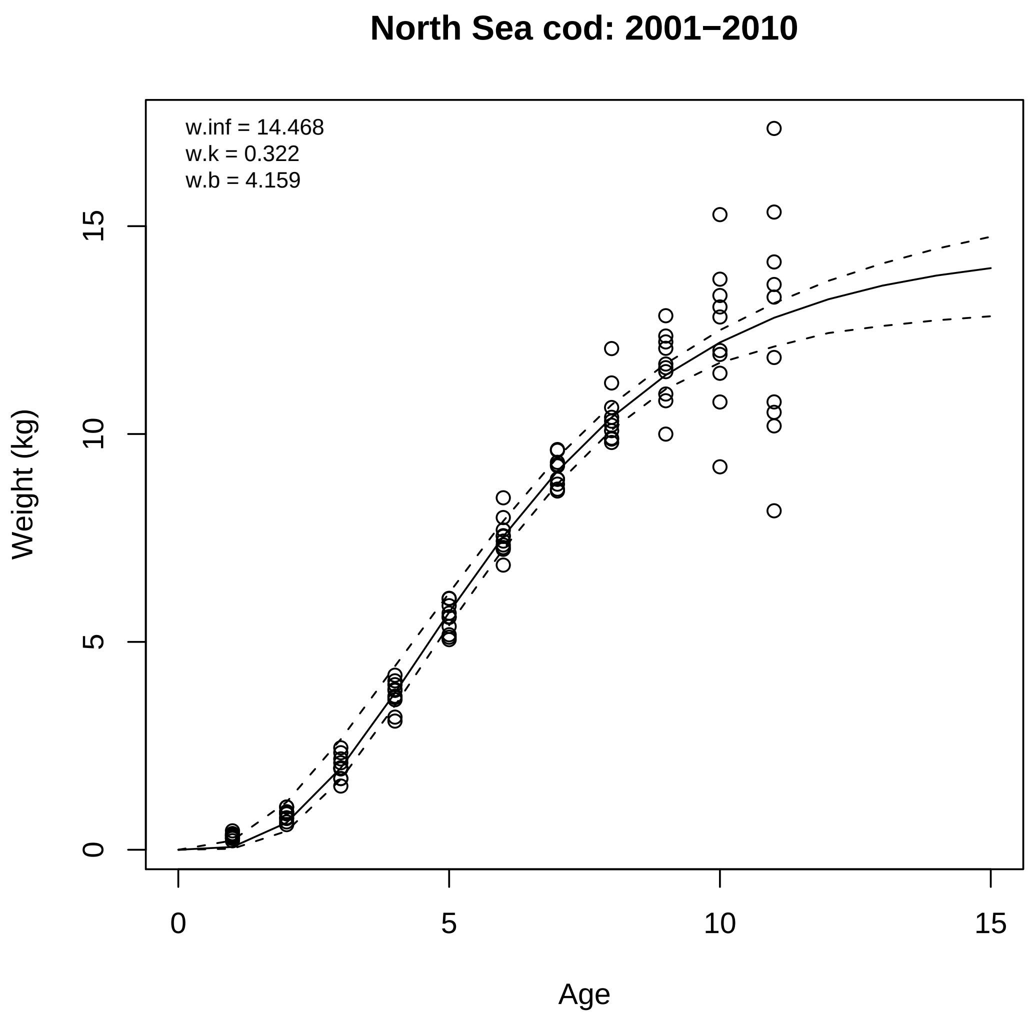


Figure 20.1: Estimated age-weight relationship for North Sea cod. Small circles reproduce age-weight data for North Sea cod given in ICES (2011c). Lines give fitted von Bertalanffy curve (solid) with approximate 95% confidence interval (dotted). The legend indicates estimates for W_∞ (w.inf), κ_{vb} (w.k) and β_{vb} (w.b) (see Equation 20.1).

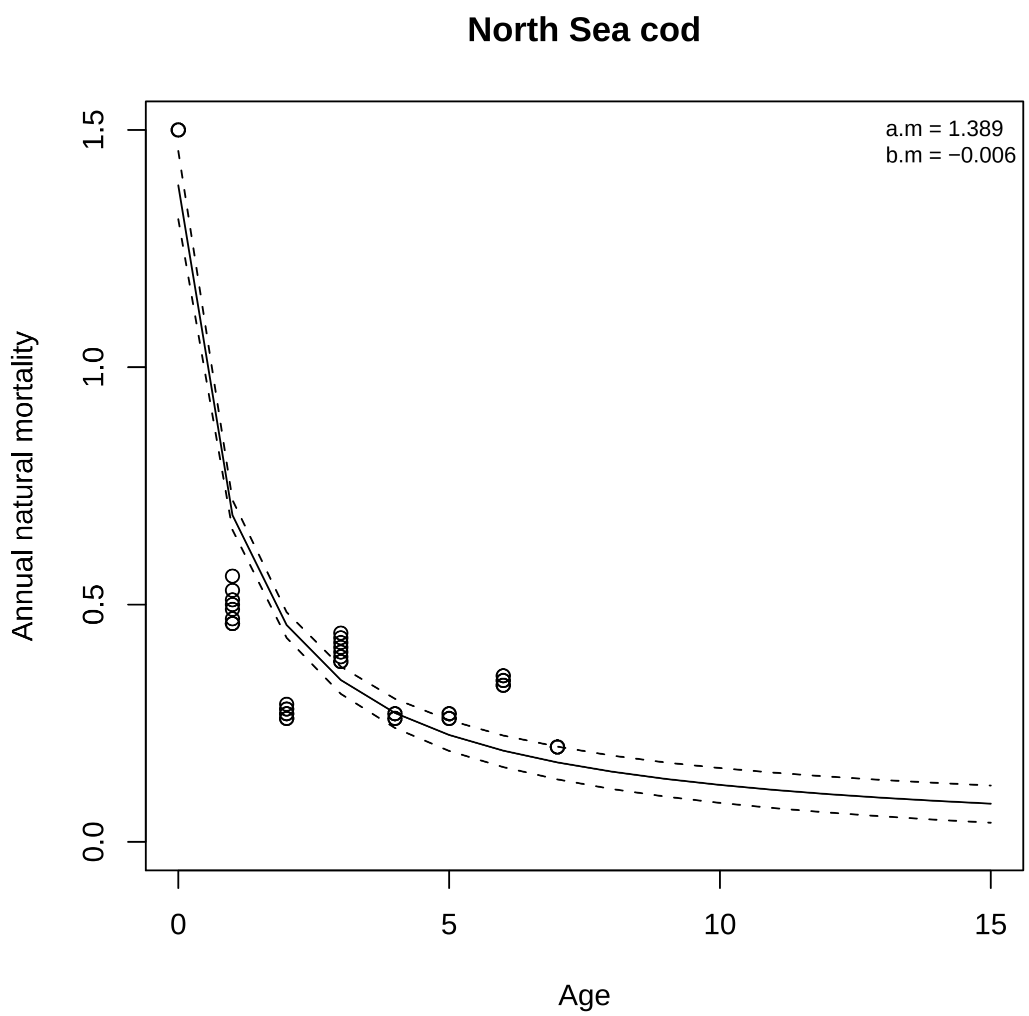


Figure 20.2: Estimated annual natural mortality M for North Sea cod. Small circles reproduce M estimates for North Sea cod given in ICES (2011c). Lines give curve (solid) with approximate 95% confidence interval (dotted). The legend indicates estimates for a_m (a.m) and b_m (b.m) (see Equation 20.3).

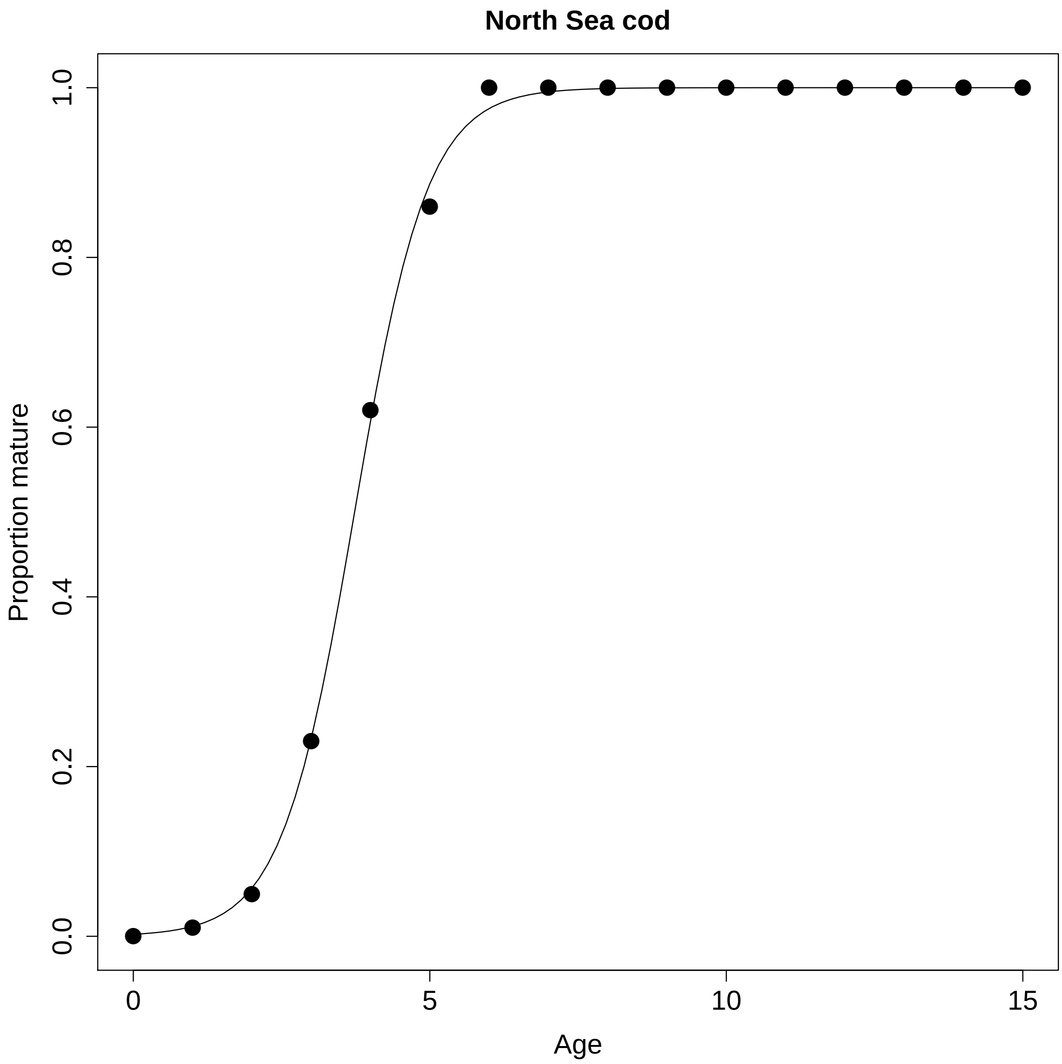


Figure 20.3: Assumed proporation mature M_a for each age for North Sea cod. Solid line gives the fitted curve from Equation 20.4. Source for estimates of M_a: ICES (2011c).

20.4 CARRYING CAPACITY

In many fish stocks, individuals of different sizes are not distributed evenly across the habitable range (Horne and Schneider 1997, ICES 2011c) There will often be clearly-defined nursery areas, in which most fish will be juveniles apart from an influx of larger adults at spawning time (Pastoors et al. 2000), and there may be specific feeding areas in deeper water which are only used by large individuals. These uneven size distributions can have a significant impact on the location of fishing activity: vessels targetting larger fish might preferentially avoid nursery areas, for example.

In the simulation, I have implemented a caricature of this feature by defining different carrying-capacity functions for different water depths. The maximum number of fish (across all ages) that each sea hex can hold was fixed to 10000 (that is, twice the mean of recent implied North Sea cod recruitment; see Section 20.5). A beta distribution (scaled to lie across the available ages in the simulated population) is used to define the maximum permitted number of fish at each age that can be found in each hex, and the parameters of the beta distributions are different for different depths. In this way, I generate an uneven age distribution of fish in different areas such as I would expect to find in reality. The general beta distribution for ages a with shape parameters α_{cc} and β_{cc} is given by

$$B_a \sim \frac{\Gamma(\alpha_{\mathrm{cc}} + \beta_{\mathrm{cc}})}{\Gamma(\alpha_{\mathrm{cc}})\Gamma(\beta_{\mathrm{cc}})} a^{\alpha_{\mathrm{cc}}-1}(1-a)^{\beta_{\mathrm{cc}}-1} \tag{20.5}$$

for $\alpha_{\mathrm{cc}} > 0$, $\beta_{\mathrm{cc}} > 0$, $0 \leq a \leq 1$ and $\Gamma(\alpha_{\mathrm{cc}}) = \int_0^\infty t^{\alpha_{\mathrm{cc}}-1} \mathrm{e}^{-t} dt$. For use in the simulation, I rescaled the beta distribution so that $0 \leq a \leq 15$ and $\sum_a B_a = 10000$ as required.

In future work, the parameters of the beta distributions could be derived from observed age- or length-frequency data from different locales. For this first implementation of the simulation, I have chosen beta-distribution parameters in order to generate specific characterstics. The parameters are summarised in Table 20.4, and the resultant carrying-capacity beta distributions across ages are given in Figure 20.4.

Depth	α_{cc}	β_{cc}	Characteristic
Shallow (-50 m)	1	3	Mostly younger fish ($a \leq 5$)
Medium (-100 m)	2	2	Mostly medium-aged fish ($5 < a < 10$)
Deep (-200 m)	3	1	Mostly older fish ($a \geq 10$)

Table 20.4: Carrying-capacity beta distribution parameters for North Sea cod.

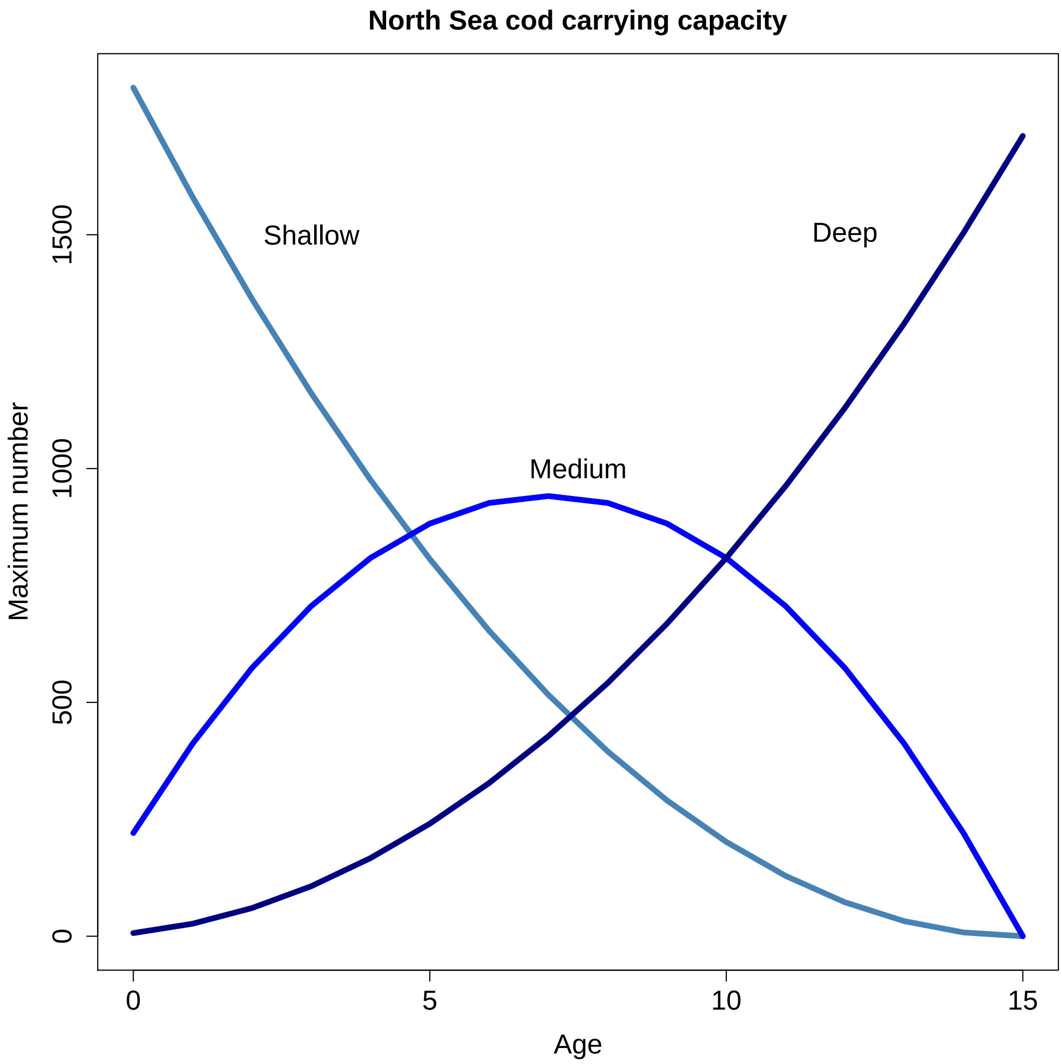


Figure 20.4: Assumed carrying capacities by age for North Sea cod, for three depths (shallow, medium, deep). The total carrying capacity in each case is 10000 fish.

20.5 RECRUITMENT

The Ricker stock-recruitment model (Ricker 1958) has been used for many years by ICES assessment working groups to attempt to characterise the relationship between spawning-stock biomass B and subsequent recruitment R, and thereby to try to improve stock forecasts for managers (Needle 2002). In particular, the Ricker model is used to generate forecasts for North Sea cod recruitment at age 1 in year y (ICES 2011c), which I denote here by R'_y. For my simulation, I need to characterise (and then generate) recruitment at age 0 (which I denote here by R_y), as that is the first age in the model. In order to generate representative values for R_Y on which to base the Ricker model fit, I back-tracked values of R'_y from ICES (2011c) by one year, using the fixed values of natural mortality $M_{0,y}$ (see Section 20.2), so that

$$R_y = R'_y \mathrm{e}^{M_{0,y}}. \tag{20.6}$$

The standard formulation for the Ricker model is

$$R_y = \alpha_r B_y \exp\left(-\beta_r B_y\right), \tag{20.7}$$

where R_y is recruitment in year y, B_y is the parental spawning stock biomass (here I assume recruitment to the fished population at age 0), and α_r and β_r are parameters to be estimated. To do this, Equation 20.7 is linearised by applying a log transform to both sides,

$$\begin{aligned} \ln\left(\frac{R_y}{B_y}\right) &= \ln\alpha_r - \beta_r B_y \qquad (20.8)\\ &= b_0 + b_1 B_y. \end{aligned}$$

I estimate parameters b_0 and b_1 using the `lm` function in R, and backtransform using

$$\alpha_r = \exp\left(b_0\right) \tag{20.9}$$

$$\beta_r = -b_1. \tag{20.10}$$

This gives the fitted Ricker curve. Approximate 95% confidence intervals about the curve are generated using the same bootstrap process as used for weights-at-age (see Section 20.1, and Needle and Hillary 2007). The fitted Ricker model for North Sea cod is shown in Figure 20.5.

I intended to use this fitted model to generate recruitment in the fisheries simulation model. However, initial trials demonstrated a problem with this particular curve. Consider the first derivative w.r.t. B of the Ricker model,

$$\frac{dR}{dB} = -\alpha_r \mathrm{e}^{-\beta_r B}\left(\beta_r B - 1\right). \tag{20.11}$$

Setting this to zero and solving for B gives the value of spawning-stock biomass at which the Ricker curve reaches its maximum,

$$B_{\max} = \frac{1}{\beta_r}. \tag{20.12}$$

The corresponding maximum recruitment is then

$$R_{\max} = \frac{\alpha_r}{\beta_r \mathrm{e}^1}. \tag{20.13}$$

For the model fit shown in Figure 20.5, $\hat{\alpha}_r = 15.310$ and $\hat{\beta}_r = 3.462 \times 10^{-5}$, giving

$$(B_{\max}, R_{\max}) \sim (2888, 16269). \tag{20.14}$$

This point is well outside the observed data range for this stock. In the simulation, this linear increase in R with increasing B means that both increase very rapidly, leading to a simulated stock which bears little resemblence to that characterised by the stock-recruitment data in Figure 20.5. To account for this, a dummy Ricker stock-recruitment curve was defined by setting the maximum $(B_{\max}, R_{\max}) = (100, 2000)$. Applying Equations 20.12 and 20.13 gave

$$(\alpha_r, \beta_r) = (54.367, 0.010). \tag{20.15}$$

This new curve is also shown in Figure 20.5, and was used subsequently in simulations with the inclusion of a noise term, so that

$$R'_y = R_y \mathrm{e}^{\varepsilon} \tag{20.16}$$

where $\varepsilon \sim \mathrm{N}\left(0, \sigma_r^2\right)$ and the standard deviation σ_r is fixed at 0.25. Recruitment is assumed to occur at the start of the first week of each year.

I note also that there are no mature fish in the population at the start of each simulation, so the application of the Ricker model in the first year would generate zero recruitment. To circumvent this, recruitment R_1 in the first year is fixed at 2000, which is roughly four times the mean of the estimated North Sea cod recruitment (in millions) during 2001-2010 (see Figure 20.5).

Finally, a spawning depth for each stock is defined (for the cod-like stock it is shallow water at 50 m), and the number of spawning locations is determined. For the simple one-stock simulation, I used only one spawning location, but this is flexible. Once the spawning locations have been determined at the start of each simulation, they do not move thereafter.

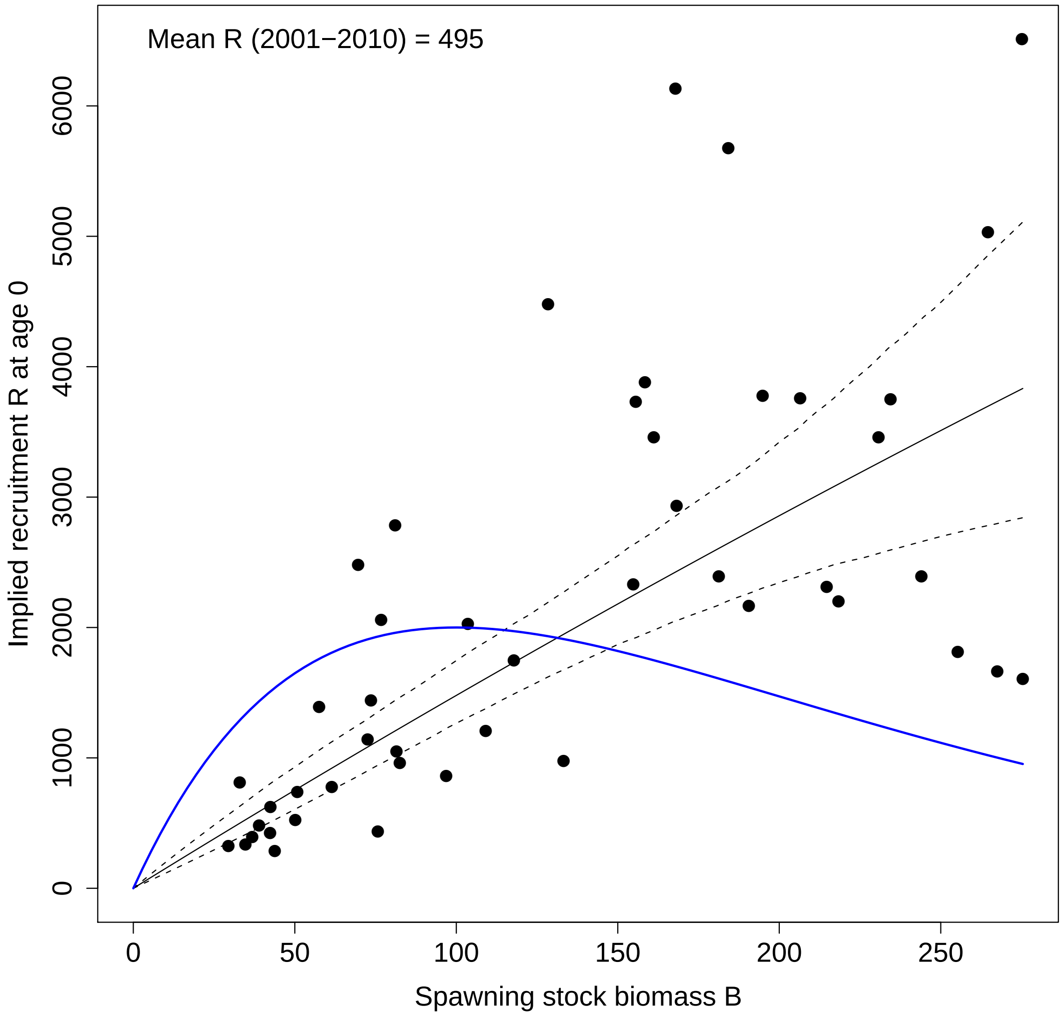


Figure 20.5: Fitted Ricker stock-recruit model for North Sea cod (solid line), with approximate 95% confidence intervals (dashed lines) generated by a parameter bootstrap. The Ricker model used in the simulations (see text for details) is shown by a solid blue line.

20.6 OVERCAPACITY AND RANDOM DISPERSION

Figure 20.6 shows an example of the start point of a simulation. The first step is for a large recruitment event to occur, in which 2000 fish of age 0 appear at the spawning location. However, this will be too many fish for the capacity of the spawning-location hex: Figure 20.4 shows that the maximum number of age-0 fish that any shallow hex can hold is 1814 (note that here I am using the term *fish* as a shorthand for *fish from the simulated cod-like stock*). Hence, the second step is to apply overcapacity dispersion, as follows.

Consider a hex h, with row and column number $\left(h_i, h_j\right)$. For each age a, hex h contains n_a^h fish. I calculate the difference D_a^h, between n_a^h and the permitted maximum carrying capacity N_a^h of the hex (from Equation 20.5). D_a^h then represents the overcapacity fish of age a that are currently in hex h. At this point, I also calculate the convergence criterion $\delta = \sum_{a,h} D_a^h$ (that is, the overcapacity fish summed across all ages and hexes). The next stage is to split the D_a^h fish into six equal parts, and move each part from hex h into each of the six neighbouring hexes (as defined by the appropriate hex movement schedule: see Figure 17.3). If the intended destination hex is land or outwith the boundary of the map, the movement will not occur, but it *will* occur if the movement would lead to the destination hex becoming overcapacity. The dispersion process is carried out for all sea hexes, and then repeated iteratively until the convergence criterion δ falls below 1814 (so some remaining overcapacity fish are permitted: insisting that $\delta \to 0$ can lead to endless loops).

The result of this initial overcapacity dispersion can be seen in Figure 20.7. I note that this approach lacks biological realism, as repeated movement can see individual groups of fish moving much further than would actually be possible in the given timeframe. However, I would argue that the approach generates appropriate dispersal on the scale of the population as a whole, and as I am not trying to model the survival characteristics of individual fish, this type of dispersion (or diffusion) is probably reasonable.

Each week in the simulation also included a *random dispersion* step. This functioned in much the same way as the overcapacity dispersion, except that a proportion of fish at each age in each hex could move away from that hex whether overcapacity or not. The proportion was determined stochastically for each age a, year y and hex h using

$$\rho_{a,y,h} \sim \mathrm{U}\left(\frac{1}{2}\rho_{\max}, \rho_{\max}\right) \tag{20.17}$$

and then the number of fish of age a in year y and hex h to be moved was determined as

$$P_{a,y,h} = \rho_{a,y,h} N_{a,y,h}. \tag{20.18}$$

The direction of movement was generated in the same way as for overcapacity dispersion. Following initial trials, the maximum dispersion rate $\rho_{\max}$ was set to 0.25. Random dispersion can lead to hexes being overcapacity for certain ages, but to save run-times the overcapacity dispersion step was only applied once in every six months of simulation time. An example of the effect of the first random dispersion is given in Figure 20.9, which follows the first application of natural mortality (Figure 20.8). The continuation of the simulation in these plots (which as yet does not include any fishing) leads to Figure 20.10, which shows the stock situation after the first 26 weeks (half the first year).

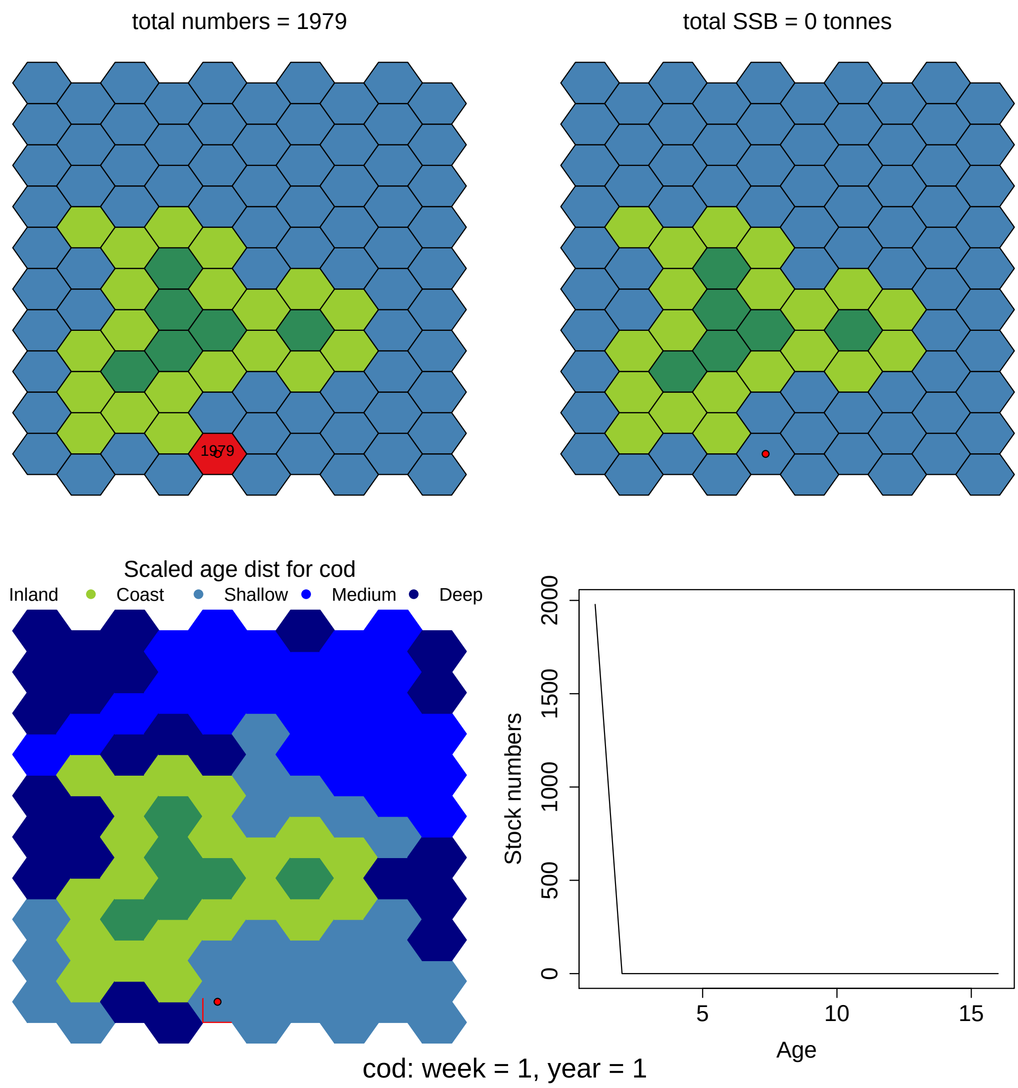


Figure 20.6: Stock summary at the start point of a simulation. Top right: total abundance N_h in each hex, summed across ages. The value of N_h is printed on each hex, and hexes are colour-coded to reflect abundance from blue (low) to red (high). Land and coast areas are marked in two shades of green. The total stock abundance is also given. Top right: as for top left, but summarising spawning-stock biomass B per hex. Spawning locations are marked with red dots. Bottom left: bathymetry with superposed age distributions in red (along with the spawning location). These distributions are scaled so that the maximum bar height is always the same. Bottom right: age distribution for whole stock.

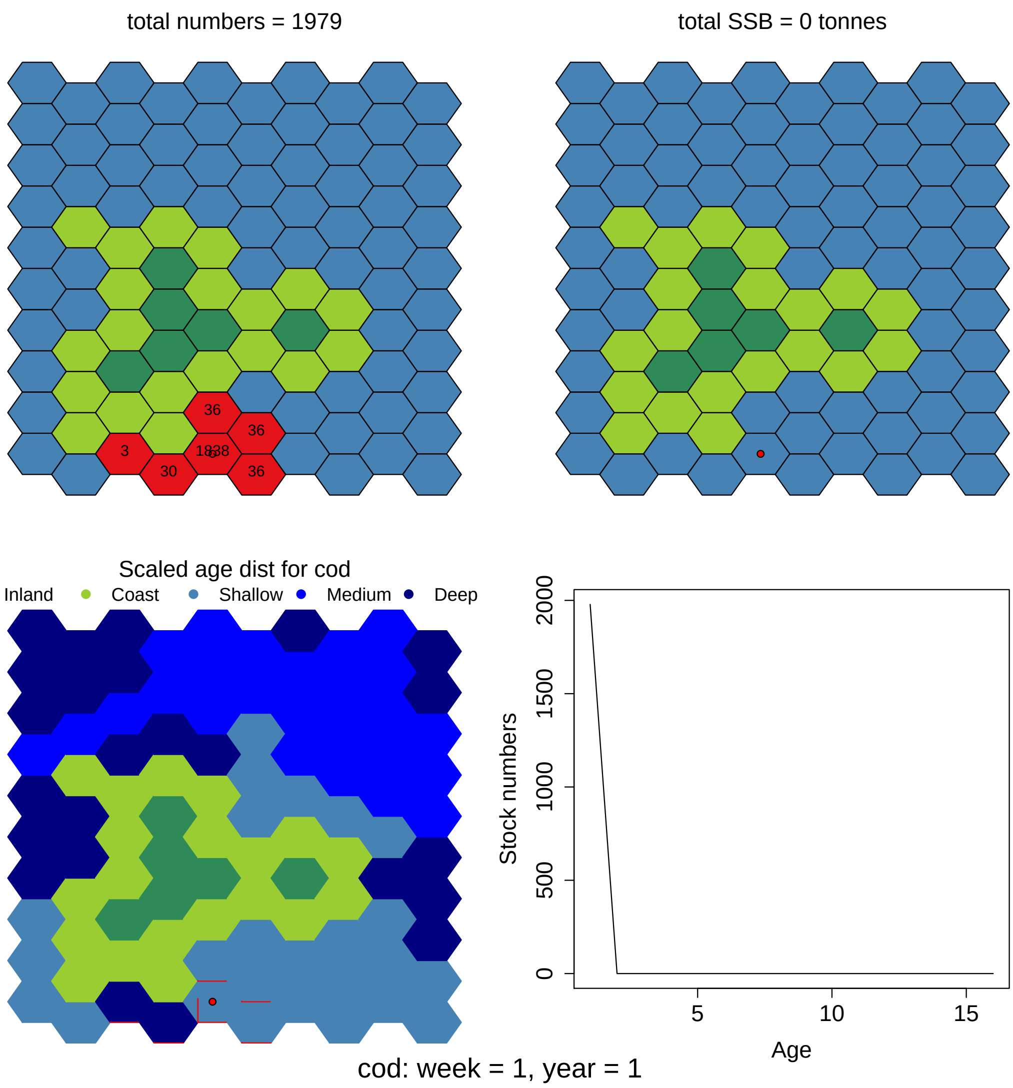


Figure 20.7: Stock summary after the first overcapacity dispersion. See caption to Figure 20.6 for details.

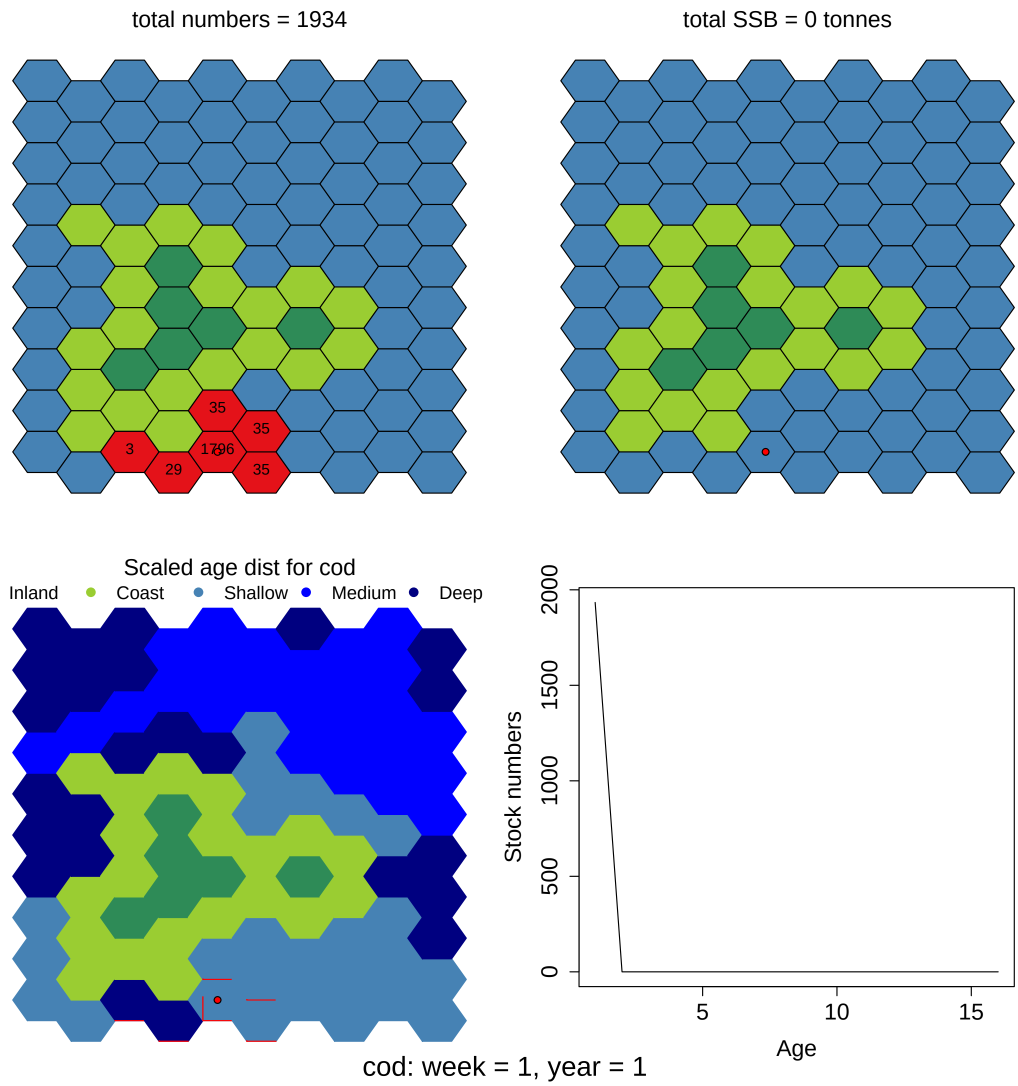


Figure 20.8: Stock summary after the first application of natural mortality and growth (although the consequences of growth in this first week are not apparent in SSB, as both maturity and weight are still extremely low). See caption to Figure 20.6 for details.

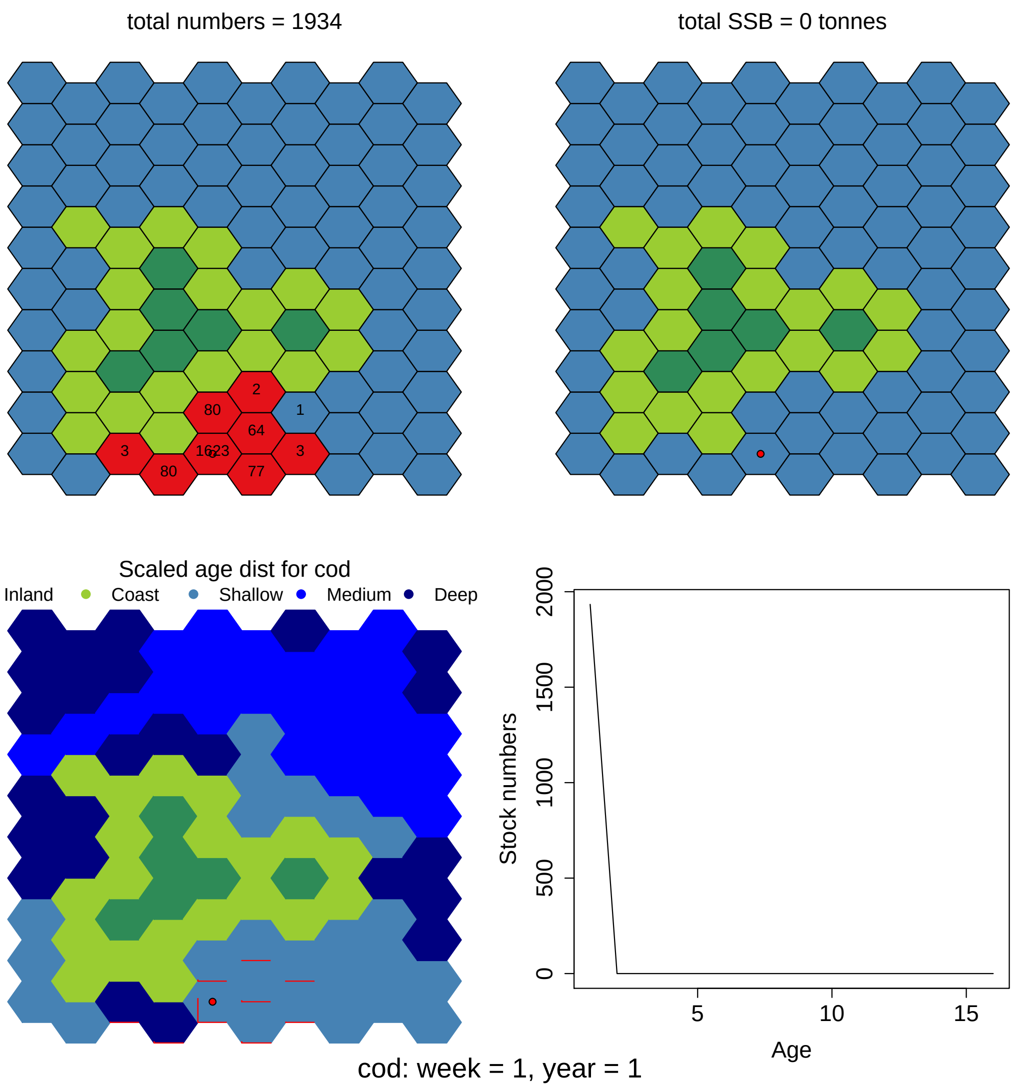


Figure 20.9: Stock summary after the first application of random dispersion. See caption to Figure 20.6 for details.

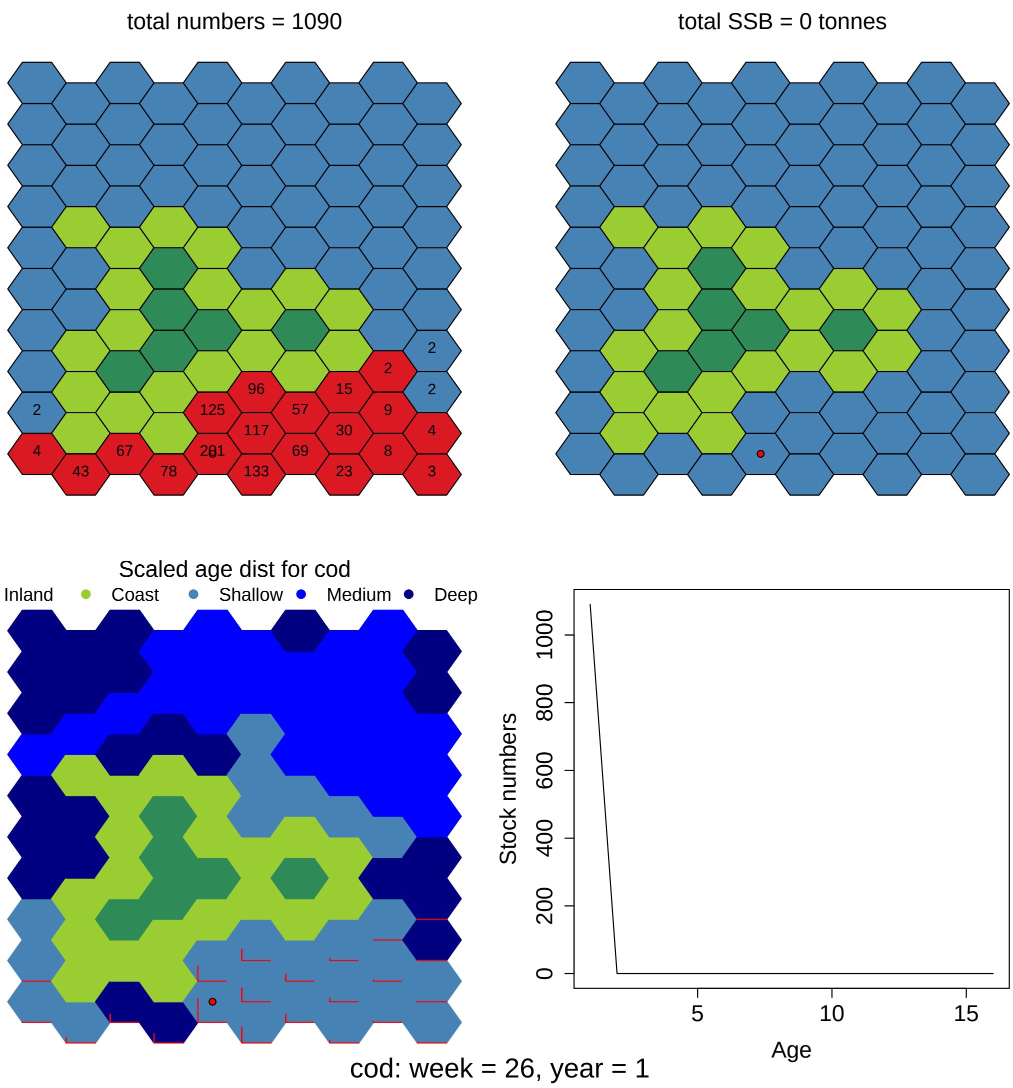


Figure 20.10: Stock summary at the start of week 26 in the first year. See caption to Figure 20.6 for details.

20.7 FISHING

A spatial simulation of one or more fish populations cannot be used to address issues of fisheries management without the ability to simulate one or more fishing vessels. Consider the simplest case of one vessel (although, as for the simulated stock(s), vessel data is held in a list in R and so is readily extendible to two or more vessels). The following settings and data objects are required in order to be able to add this vessel to the simulation:

Start year The vessel is not allowed to start fishing until a number of years have elapsed in the simulation, in order to let the fish populations settle into an equilibrium (albeit a fluctuating one). In trials, the start year was set to $y = 5$.

Home port The location of the home port of the vessel is randomly selected from the available coastal hexes in the simulation. To ensure that the chosen hex is suitable, the selection algorithm includes a check that more than 90% of the water hexes are accessible from the port hex. Accessability is determined by using the A* algorithm (Section 19) to check if there exist paths from the proposed home port to each and every sea hex.This prevents the home port being positioned on a lake or other inland water feature. An example is given in Figure 20.11.

Selectivity The selectivity σ_l of fishing gear (that is, the proportion of available fish in each length class that the gear would be expected to retain) is often modelled by an S-shaped curve (Beverton and Holt 1957). One formulation of this is

$$\sigma_l = \frac{1}{1 + \exp(s_1 - s_2 l)}, \tag{20.19}$$

with two parameters s_1 and s_2. The selectivity curve is often summarised by the length at which 50% and 25% of fish are retained (denoted by L_{50} and L_{25} respectively). Given these two quantities, the required parameters can be derived using

$$s_2 = \frac{\ln 3}{L_{50} - L_{25}}, \tag{20.20}$$

$$s_1 = L_{50} s_2. \tag{20.21}$$

For example, UK studies in 2001 (Barry O'Neill, Marine Laboratory, Aberdeen, *pers comm*) indicated that, for North Sea cod, $L_{50} = 29.4$cm and $L_{25} = 26.9$cm, implying that $s_1 = 12.92$ and $s_2 = 0.44$.

Although my simulation model is currently based on age rather than length, I can generate an age-based selectivity curve in a directly-analagous manner. Observations of cod lengths at age from the ICES North Sea International Bottom Trawl Survey (IBTS) data, available from the DATRAS database (`http://datras.ices.dk/`), indicate that the mean age of cod measuring 29.4 cm (L_{50}) and 26.9 cm (L_{25}) respectively is approximately

$$a_{50} = 2.0, \tag{20.22}$$
$$a_{25} = 1.0, \tag{20.23}$$

from which an age-based selectivity curve can be derived using

$$s_2^a = \frac{\ln 3}{a_{50} - a_{25}}, \tag{20.24}$$
$$s_1^a = a_{50} s_2^a, \tag{20.25}$$

and

$$\sigma_a = \frac{1}{1 + \exp\left(s_1^a - s_2^a a\right)} \tag{20.26}$$

for age a.

The resultant selectivy-at-age curve is plotted in Figure 20.12. Note that this indicates only the proportion of fish which are *retained* by the gear once in the net, and does not account for the availability of fish to the gear in the first place.

Fuel costs The cost of diesel fuel is one of the key financial impediments for modern fishing vessels (Abernethy et al. 2010). Some types of fishing (for example, beam trawling) require a large amount of fuel, while others (for example, creeling) may require less, but for all vessels expenditure on fuel is one of the main costs associated with fishing activity. The economics of fuel for fishing are complicated and the subject of an extensive literature, but for this first implementation of my simulation model it is sufficient to consider fuel costs to be a function of the number of hexes travelled in a trip: the further away the fishing grounds, the more expensive it is to get there (and back). In the simple trials described in Section 21, I have assumed that travelling one hex costs $C_t = £100$.

Fish price If fuel is the main cost of fishing activity, then clearly the main benefit (and hence source of income and potential profit) is selling the fish caught. The price of fish is another complicated variable that can change considerably from day to day due to numerous factors (both internal and external to the market), and which itself is the subject of extensive literature (see, for example Sumaila et al. 2007), but (as with fuel price) I have deemed it sufficient to consider a simple price function in which price P_a per fish is a function of the square-root of age a,

$$P_a = \phi\sqrt{a}, \tag{20.27}$$

where ϕ is a fixed constant. The shape of this relationship for $\phi = 1000.0$ is given in Figure 20.13.

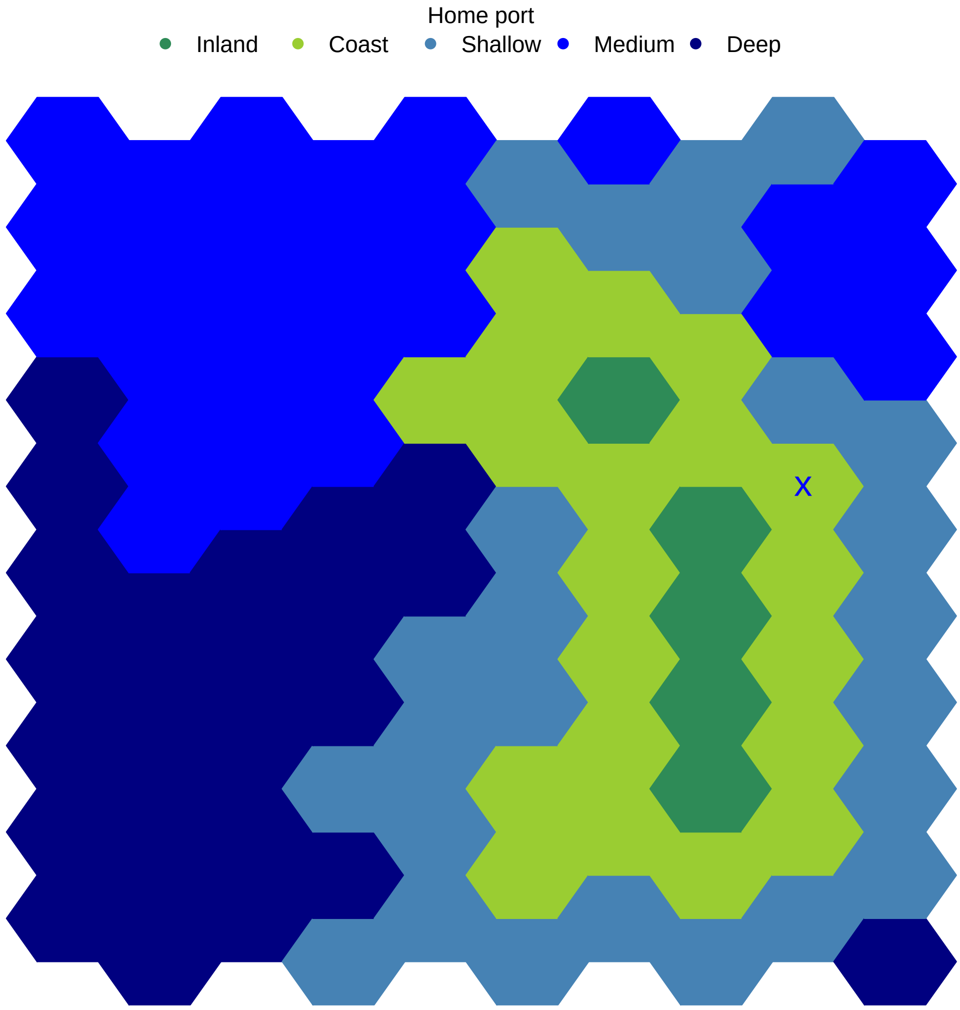


Figure 20.11: An example of a generated home port, marked with a blue cross. A hex is allowed to be a home port if vessels from that hex access at least 90% of sea hexes (in this case, all of the sea hexes can be accessed).

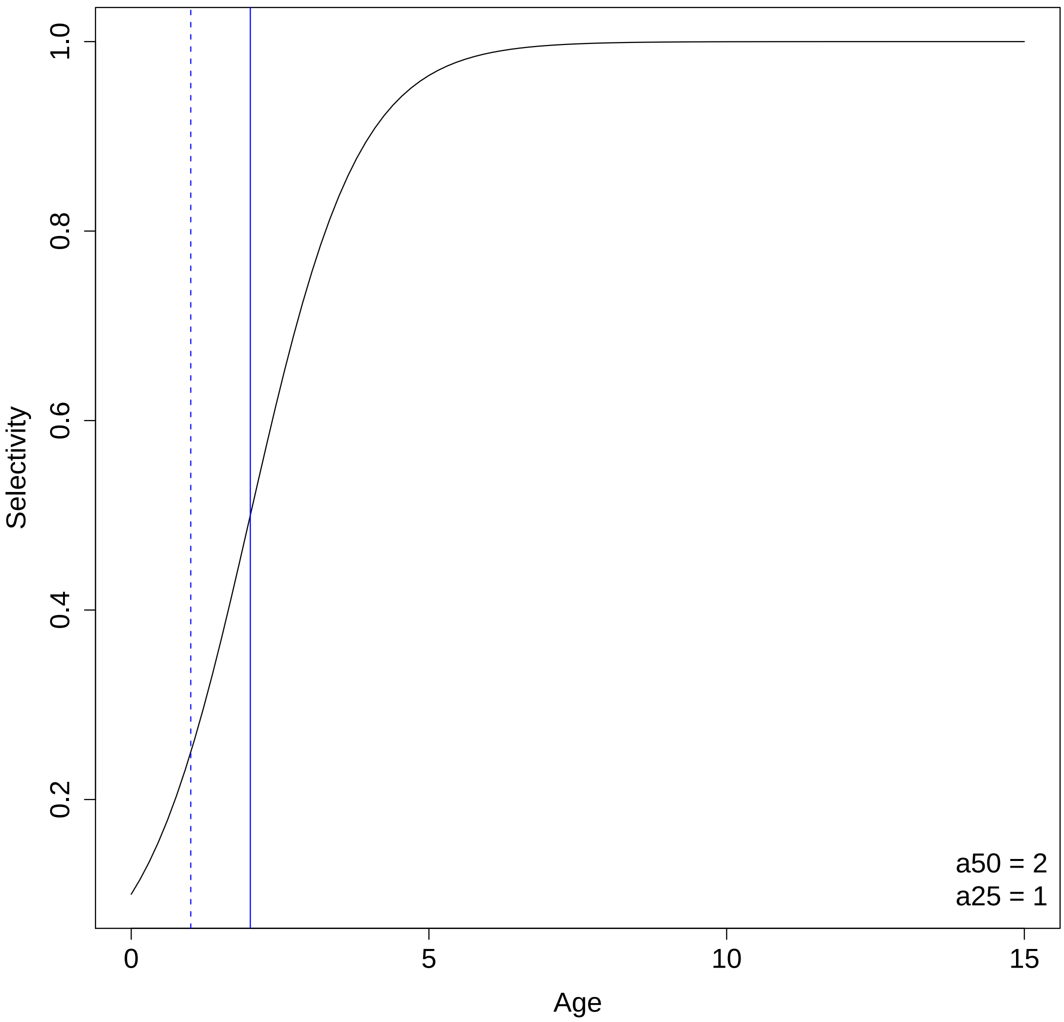


Figure 20.12: Age-based selectivity σ_a for a UK-type vessel fishing on North Sea cod.

Once fishing parameters have been defined, the activities of the fishing vessel can be simulated within the wider fisheries model. For this implementation, the fishing location for the vessel for each week is determined as follows:

1. The vessel is assumed to start each week at the home port.
2. A search is carried out to determine the fishing location for that week. For each sea hex, the A* algorithm (Section 19) is applied to determine the number of hexes h_n that would need to be traversed for the vessel to reach that hex (so that $2h_n$ hexes need to be crossed if the return journey is also included). Then the

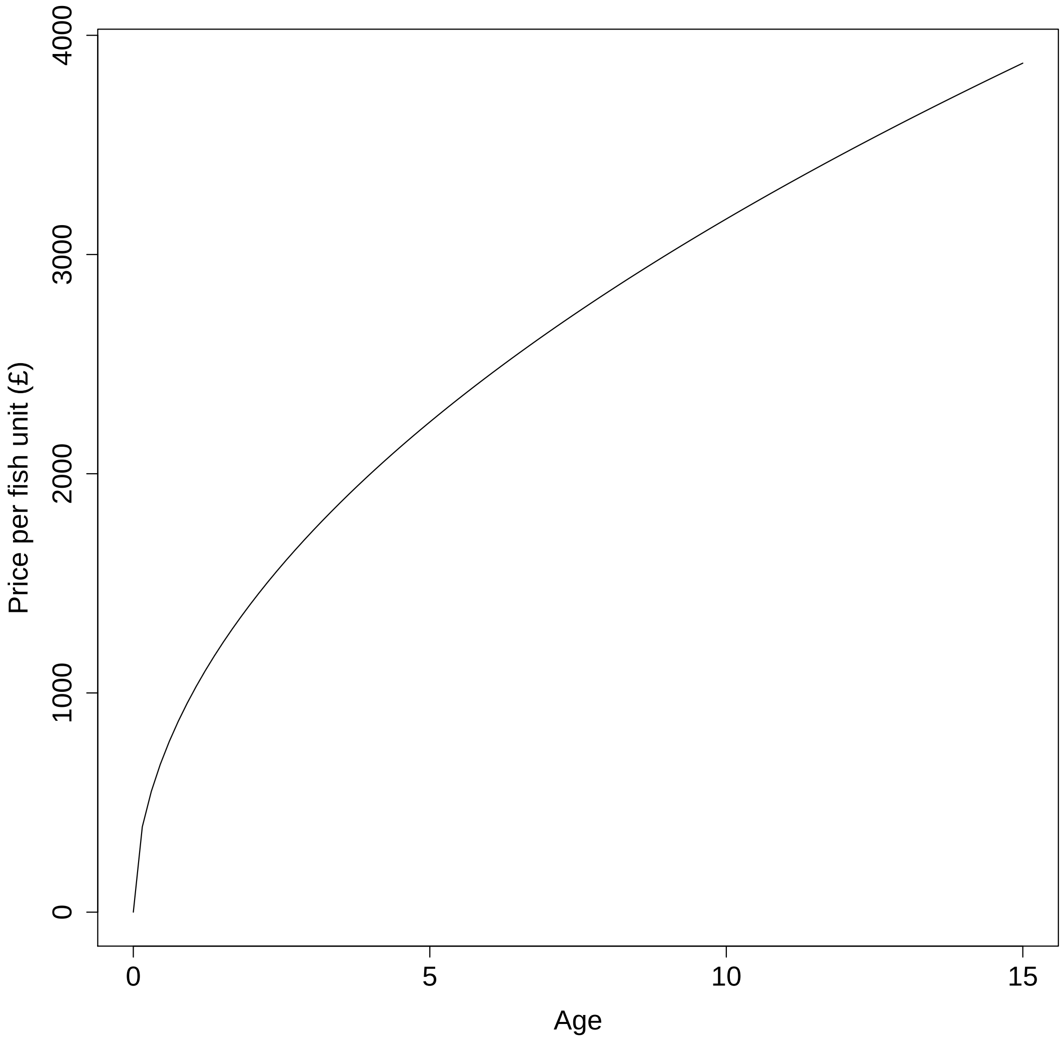


Figure 20.13: Example of an age-based fish price curve, based on Equation 20.27 with $\phi = 1000$.

cost of fishing in that hex is given by

$$C_h = 2C_t h_n. \tag{20.28}$$

3. Next, the vessel's selectivity curve σ_a is applied to the current age distribution $N_{a,h}$ of fish in that hex, to determine the expected catch $Y_{a,h}$ that the vessel would return with if that hex was chosen:

$$Y_{a,h} = \sigma_a N_{a,h}. \tag{20.29}$$

Note that here I am assuming that the skipper of the vessel has perfect knowledge of the age distribution of every hex in the simulation: this could be modified to model uncertainty, which would be much more realistic. Given $Y_{a,h}$, the expected *price* of the fish to be caught is calculated as

$$P_h = \sum_a P_a Y_{a,h}. \tag{20.30}$$

4. Finally, the profit (or loss) to be expected from fishing in hex h is generated as

$$D_h = P_h - C_h. \tag{20.31}$$

   This calculation is repeated for each sea hex in the simulation, and the hex which meets the economic requirements of the vessel is chosen to be fished in that week. These requirements could be simply to maximise profit at all times, or they could be for the vessel to try and follow a pre-defined profit curve through the year. These ideas are explored further in Section 21.

5. The effect of fishing mortality on the chosen hex is modelled in a straightforward manner by removing the fish caught from the population distribution in that hex, so that

$$N_{a,h} \to N_{a,h} - Y_{a,h}. \tag{20.32}$$

20.8 THE SIMULATION ALGORITHM

The algorithm followed by the simulation is outlined in Figure 20.14. This has been implemented in R (version 2.8.1, R Development Core Team 2011) in a modular fashion, so that the code remains flexible. For example, the two simple harvest control rules (HCRs) currently included are:

WPM *Weekly profit maximisation:* In this mode, the vessel selects the hex that returns the greatest profit for that week.

WCQ *Weekly catch quota:* Here, the vessel selects the hex which will produce the largest catch below a predefined upper limit (and ignores the profit implications).

It is a straightforward matter to replace these in the code by any conceivable HCR that a manager may wish to be tested.

The principal drawback with the extant implementation is that it is coded solely in R, and contains several loops. This combination leads to long run-times: the case studies presented in Section 21 below include only 10 iterations (each of 10 years with 5 fishing years on a 10×10 map), but took over $4\frac{1}{2}$ hours to run. This precludes extensive testing allowing for uncertainty and variation in (for example) recruitment, and will need to be addressed in future versions.

Figures 20.15 and 20.16 illustrate the fishing part of the algorithm for a test run in which the goal of the vessel was to maximise catch below an upper limit of 15. Firstly, Figure 20.15 summarises the stock in week 1 of the sixth year of a simulation (that is, week 261 in total), which represented the first week of fishing activity for this particular case study. Here, recruitment has just taken place on the other side of the land-mass from the home port, while mature fish remain concentrated along the western edge of the map (although not necessarily close to the spawning area). Figure 20.16 then shows the hexes fished by the vessel during the first four weeks of that sixth year. In this case, the vessel is not concerned about profit, although profit is high for each of these weeks. The focus is on fishing the hex which gives the highest yield which is still less than 15, and to achieve this the vessel fishes hexes which are either north or south of the spawning hex (but avoids the spawning hex itself). To reach these hexes, the vessel passes either to the north or the south of the land-mass, whichever produces the shorter journey.

To save storage space, the plotting of weekly fishing decisions is optional, and such plots were not generated for the case-study tests presented in Section 21 below.

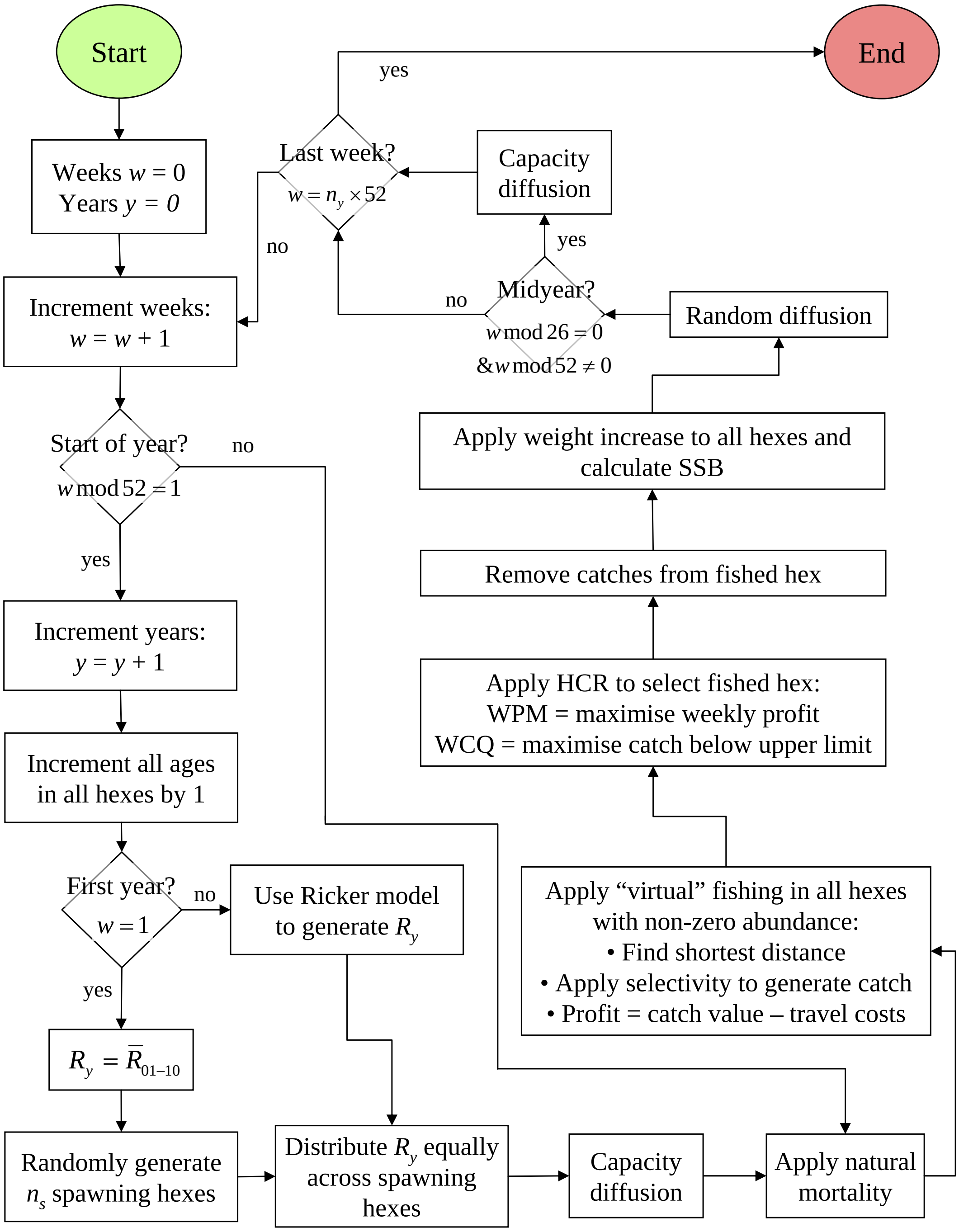


Figure 20.14: Flowchart for hex simulation.

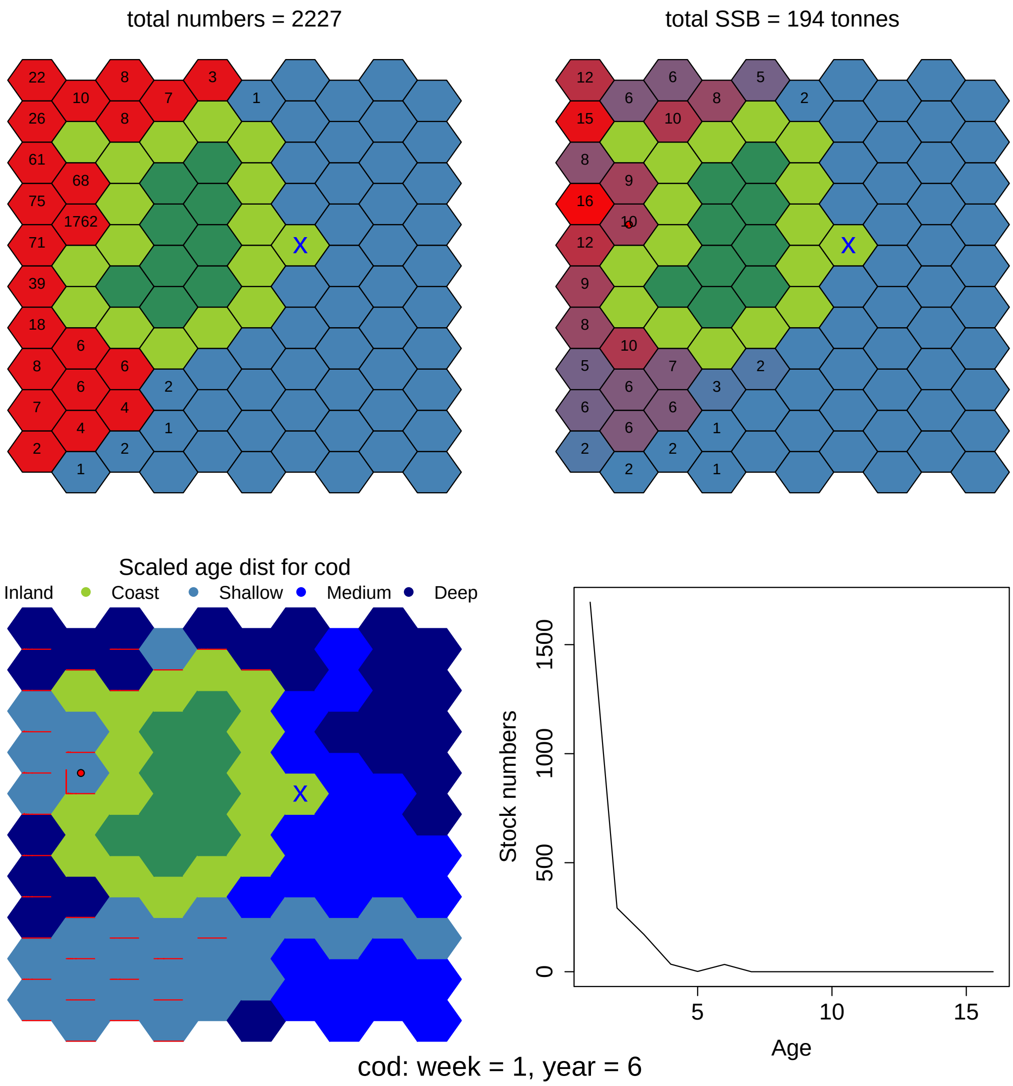


Figure 20.15: Stock summary at the start of week 1 in the sixth year, the first week of fishing for this simulation. See caption to Figure 20.6 for details. The home port is marked by a blue cross.

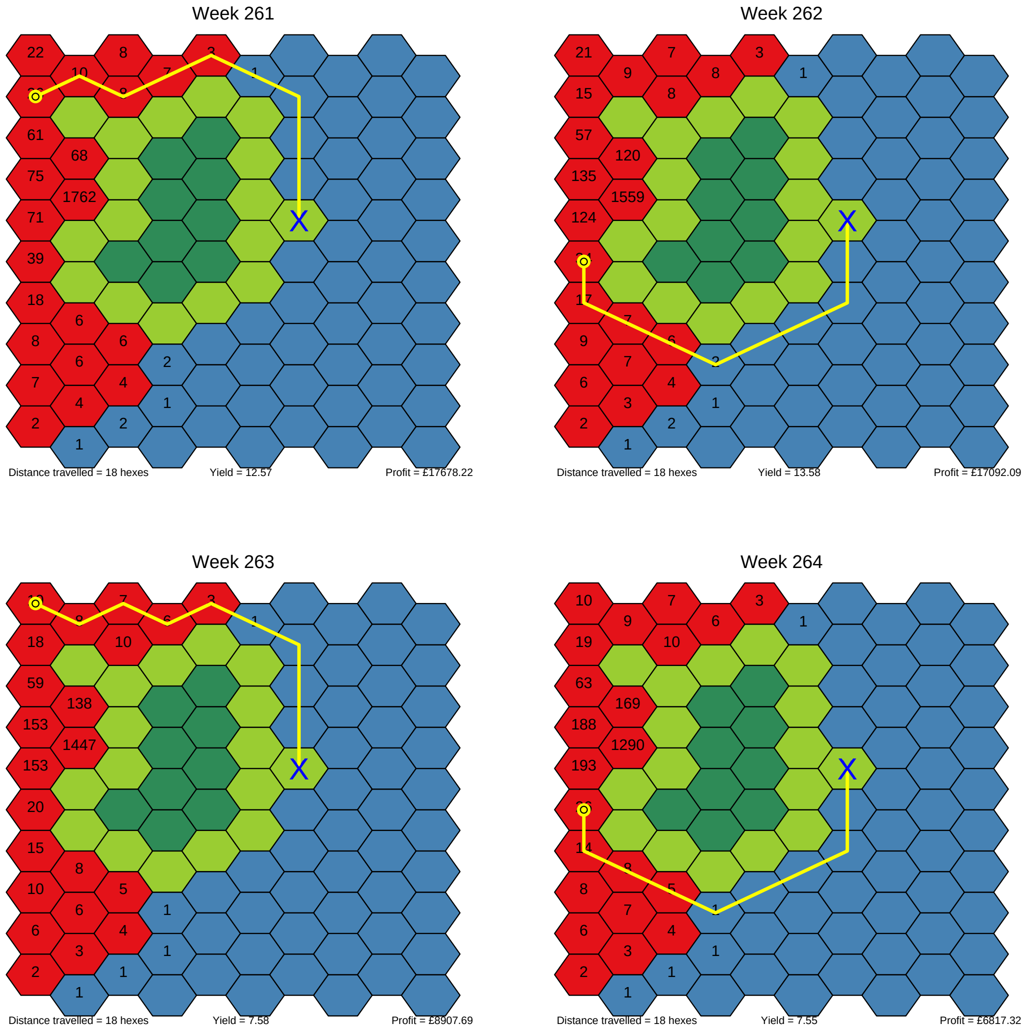


Figure 20.16: Fishing decisions taken during weeks 261-264 (the first four weeks of the sixth year) by a vessel attempting to maximise catch below an upper limit of 15. Dark green hexes are land, light green hexes are coast, and the home port is indicated by a blue cross. Numbers on hexes show total abundance, and the colour of sea hexes is scaled by abundance (blue = low, red = high). The fished hex is marked by a yellow dot, while the route taken to get there and back is given by a yellow line. For each week, the legend gives the distance travelled (in hexes), the total yield, and the generated profit.

21 Testing the simulation model

21.1 INTRODUCTION

It is not my intention in the Section to explore fully the potential of the simulation model. I anticipate that it will be flexible and powerful enough to be applicable to a very wide range of questions that fisheries managers might ask, and I cover some of these in notes on future work below (see Section 22). Here, I will present the results of two simple case studies, in which I determine whether the choice of harvest control rule between weekly profit maximisation (WPM) and weekly catch quota (WCQ; see page 269) affects catch, profit, and abundance.

The parameters of the two simulations are as follows. I use a 10×10 hex grid (so $n_h = 10$), and assume a single land mass. Stock and vessel settings are as given in Sections 20.1 to 20.7 above. The simulations are run for ten years $(n_y = 10)$, with fishing activity starting in the sixth year. Each simulation was run for ten iterations. This is a very low number: for a reasonable exploration of confidence intervals at least 500 iterations would be recommended (Davison and Hinkley 1997), but with this R implementation such a run would take over nine days of computing time (as mentioned above, around $4\frac{1}{2}$ hours were required for ten iterations). Hence, I consider these examples to be illustrative only.

21.2 WEEKLY PROFIT MAXIMISATION (WPM)

In this simulation, the vessel's approach is to fish in the hex which generates the maximum profit each week. Figure 21.1 shows the generated area for the first iteration of the WPM simulation, which features a triangular land mass with the home port at the south-west corner. Figures 21.2 to 21.4 then summarise the state of the stock immediately following recruitment (that is, in the first week of each year) in the first three of the ten years of this first iteration of the simulation, showing the stock spreading from the initial spawning area and building up a spawning-stock biomass.

Figure 21.5 gives time-series of the weekly values of total abundance, catch, spawning stock biomass (SSB), total stock biomass (TSB), and the profit generated by the vessel (which is the difference between the value of the catch each week, and the travel costs incurred in catching it). In this case, abundance goes through the anticipated annual cycle, but the overall trend is downwards from the third year onwards. SSB and TSB both rise steadily until the start of fishing activity in the sixth year, at which point they decline considerably and reach a relatively low equilibrium. Catch and profit both go through annual cycles, with the highest values of each at the start of the year when young fish are abundant. It could be hypothesised that such an inconsistent cash flow pattern would be very difficult to manage for a real commercial fishing business, but that is perhaps outwith the scope of this thesis.

The annual stock summaries in Figure 21.6 follow much the same pattern for abundance and biomass. The size of the incoming year-classes is, however, declining through time, and so what looks from Figure 21.6 to be a stable fishery may in fact be on the brink of further reductions. Finally for this first iteration, Figure 21.7 summarises the fishing locations chosen over the simulation period to maximise weekly profit. The principal focus is on the shallow water to the south-west of the map. This is where the spawning area for this stock is located (see, for example, Figure 21.2) and where the bulk of the stock remains as it grows. The fish provide the required profitability, despite the relatively long journeys required to get to that area, but at the cost of a suppressed abundance.

Similar plots were generated for each of the 10 iterations carried out for the WPM case-study simulation. I compare the results of these iterations in Figure 21.8 (weekly) and 21.9 (annual). Each of the iterations uses the same settings for stock, fishery and area, but the layout and recruitment are both randomised and this generates quite large differences between them. However, there is a strong underlying trend of SSB declining dramatically to a low level when fishing activity commences, and all iterations show a strong annual cyclicity to catch and profit.

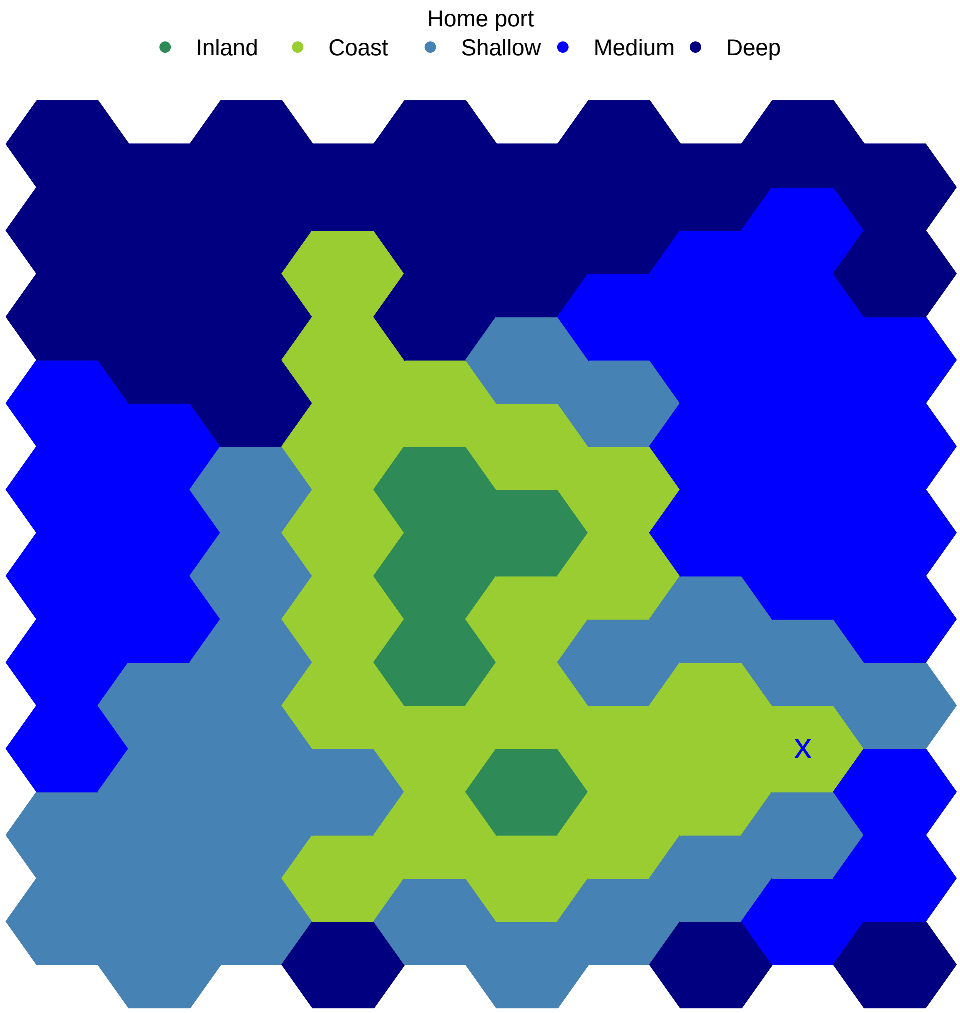


Figure 21.1: Generated sea and land hexes for the first iteration of the WPM case-study simulation. The blue cross indicates the home port.

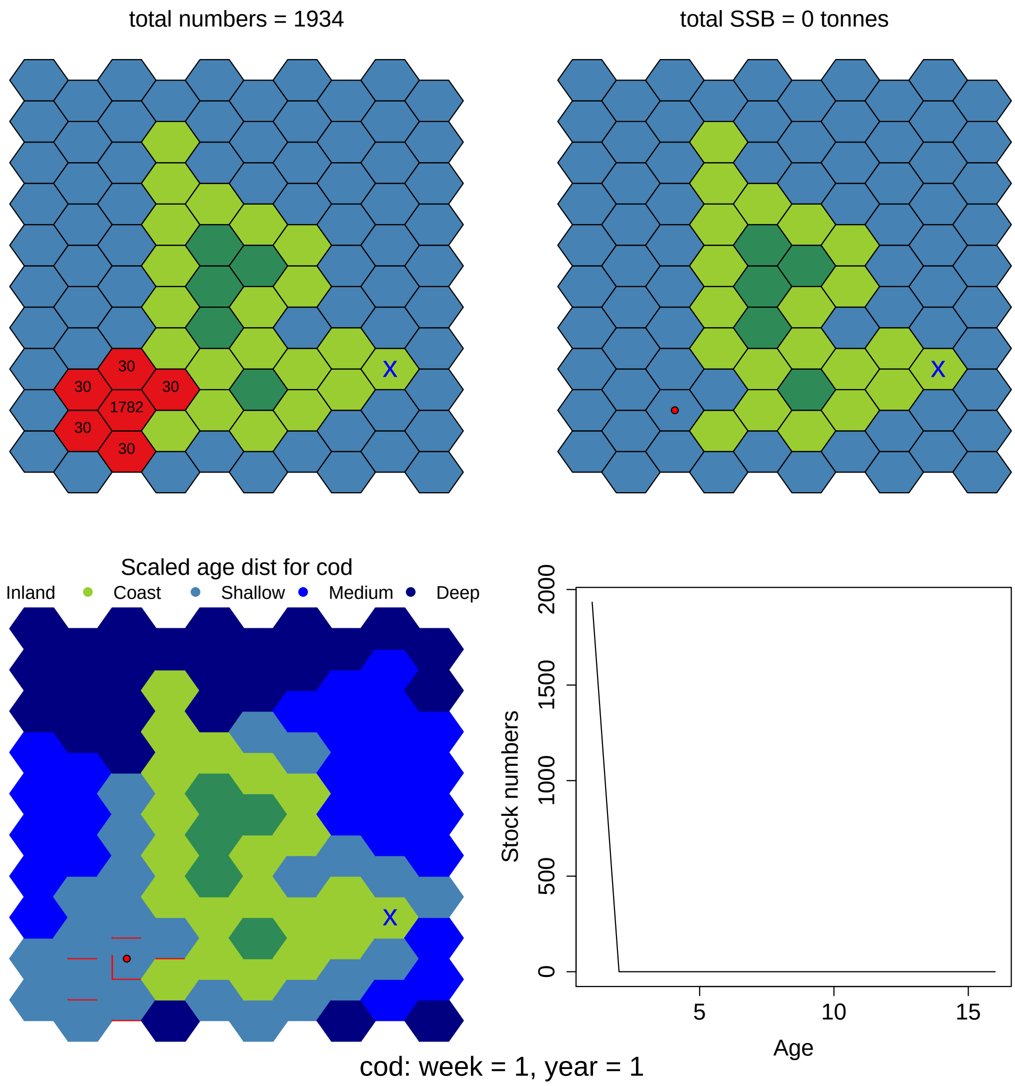


Figure 21.2: Stock summary at the start of first year of the first iteration for the WPM case-study simulation. See caption to Figure 20.6 for details.

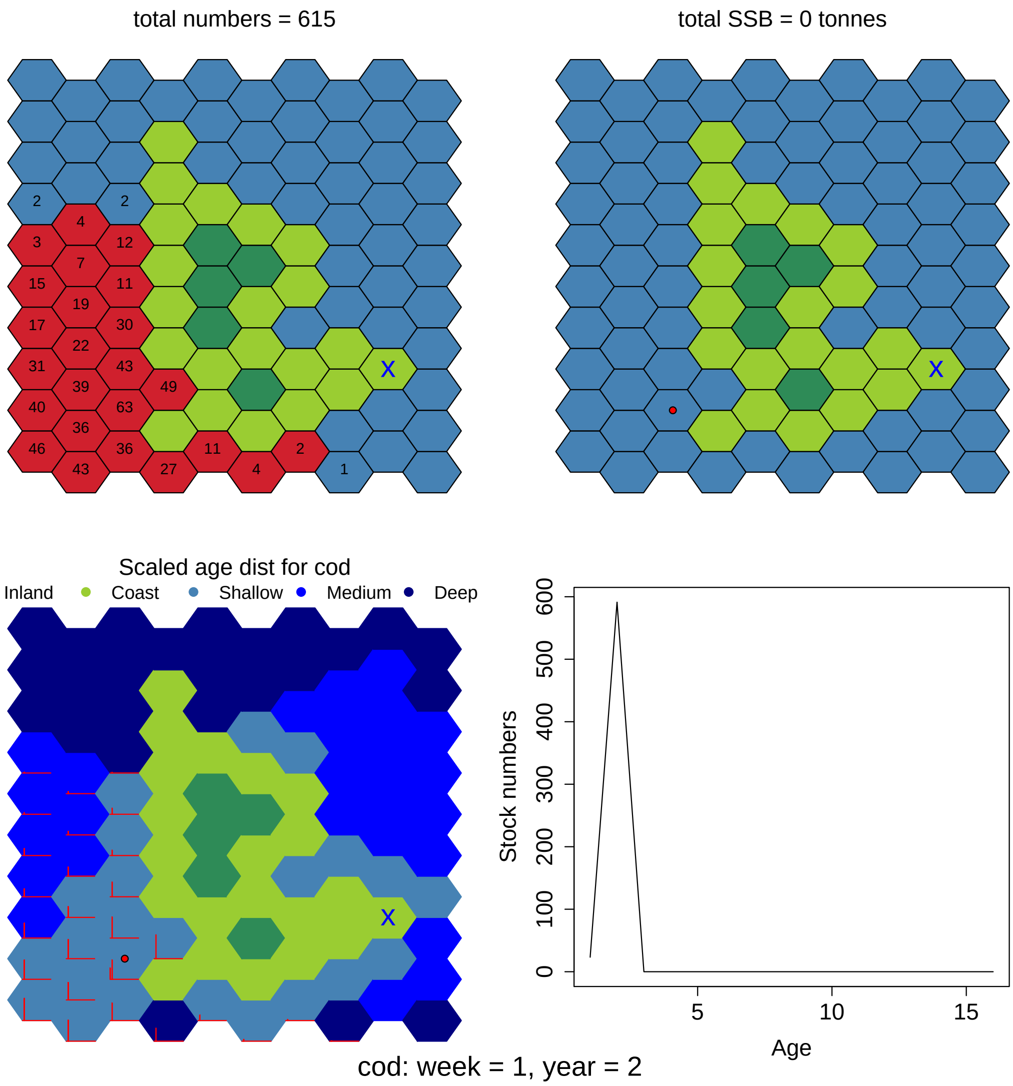


Figure 21.3: Stock summary at the start of second year of the first iteration for the WPM case-study simulation. See caption to Figure 20.6 for details.

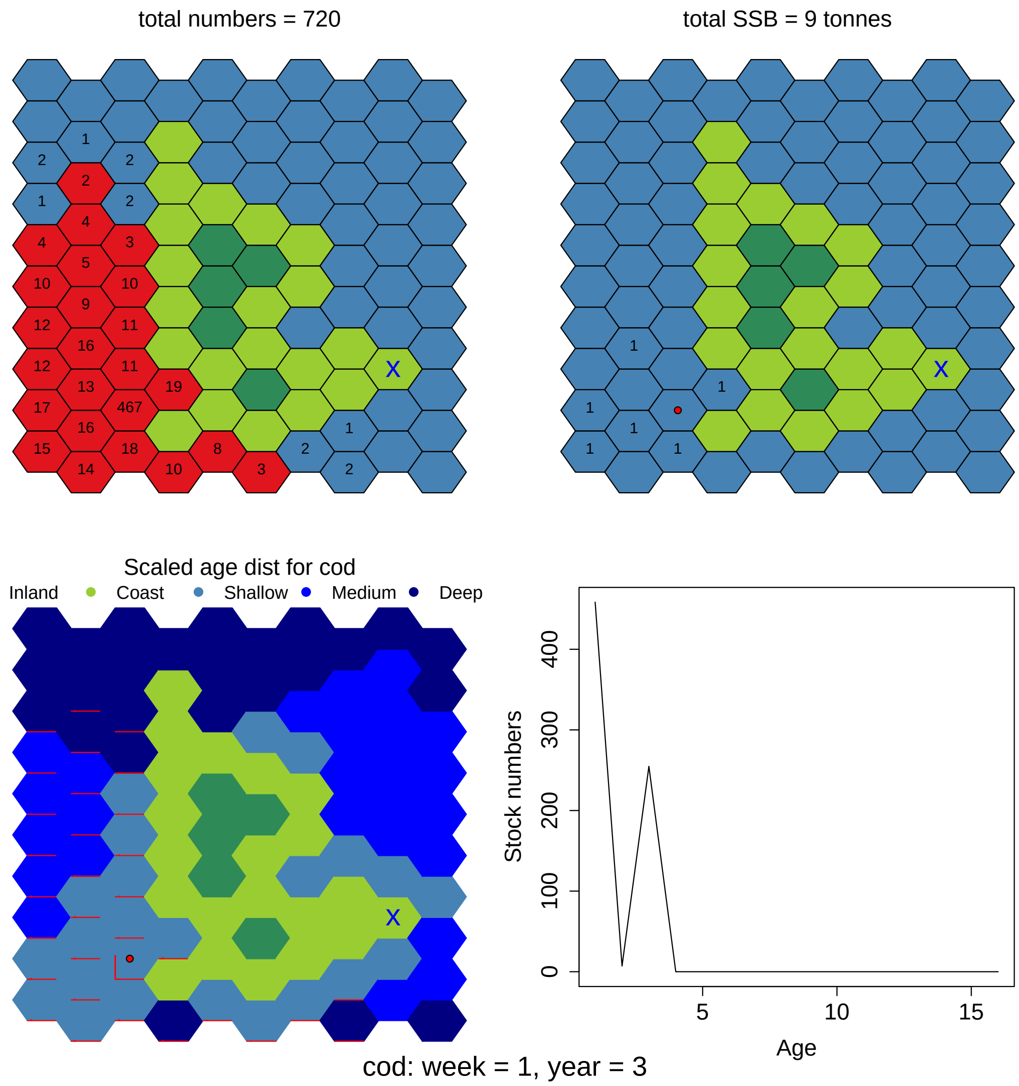


Figure 21.4: Stock summary at the start of third year of the first iteration for the WPM case-study simulation. See caption to Figure 20.6 for details.

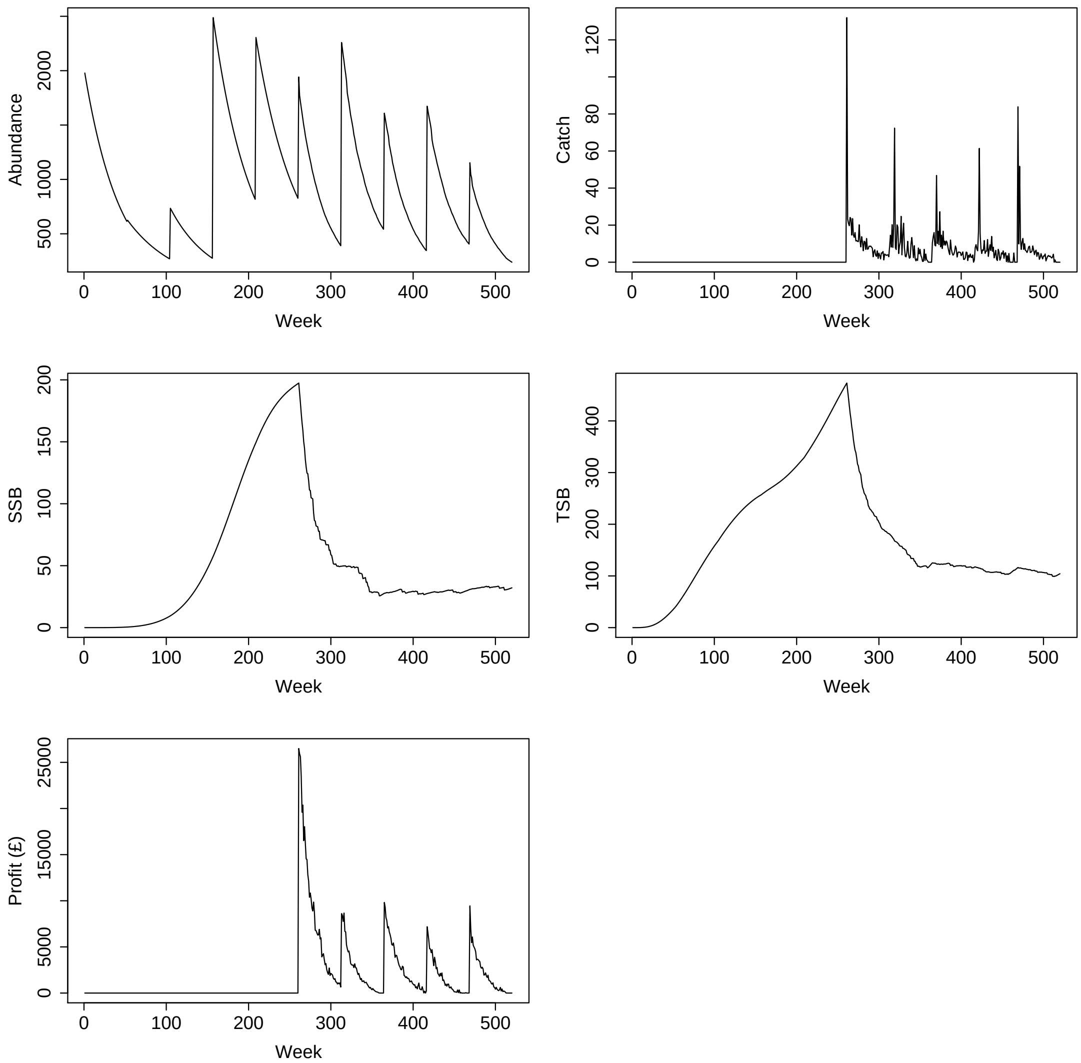


Figure 21.5: Weekly stock summaries for the first iteration of the WMP case-study simulation.

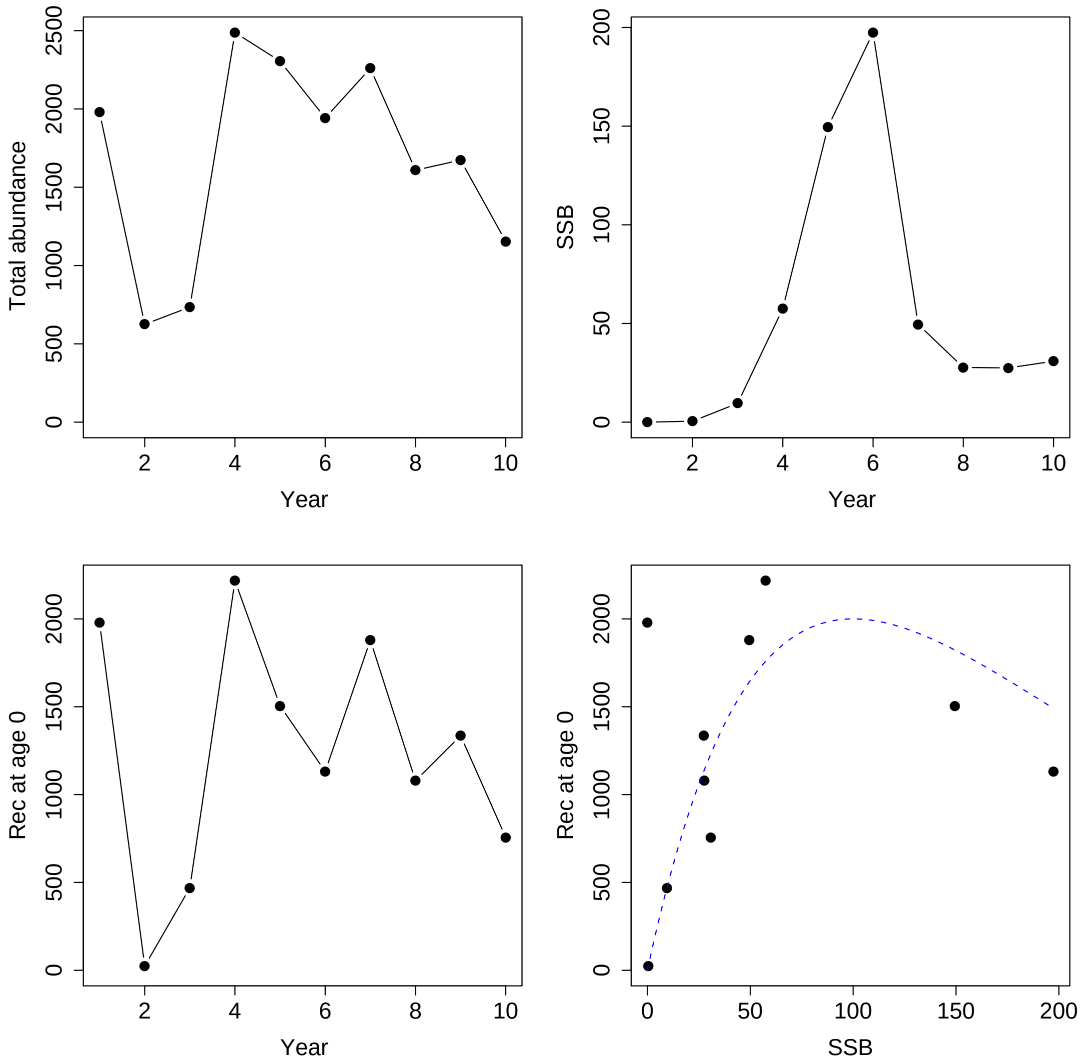


Figure 21.6: Annual stock summaries for the first iteration of the WMP case-study simulation. The blue line on the stock-recruitment plot (lower right) is the underlying Ricker curve used to generate recruitment in the simulation.

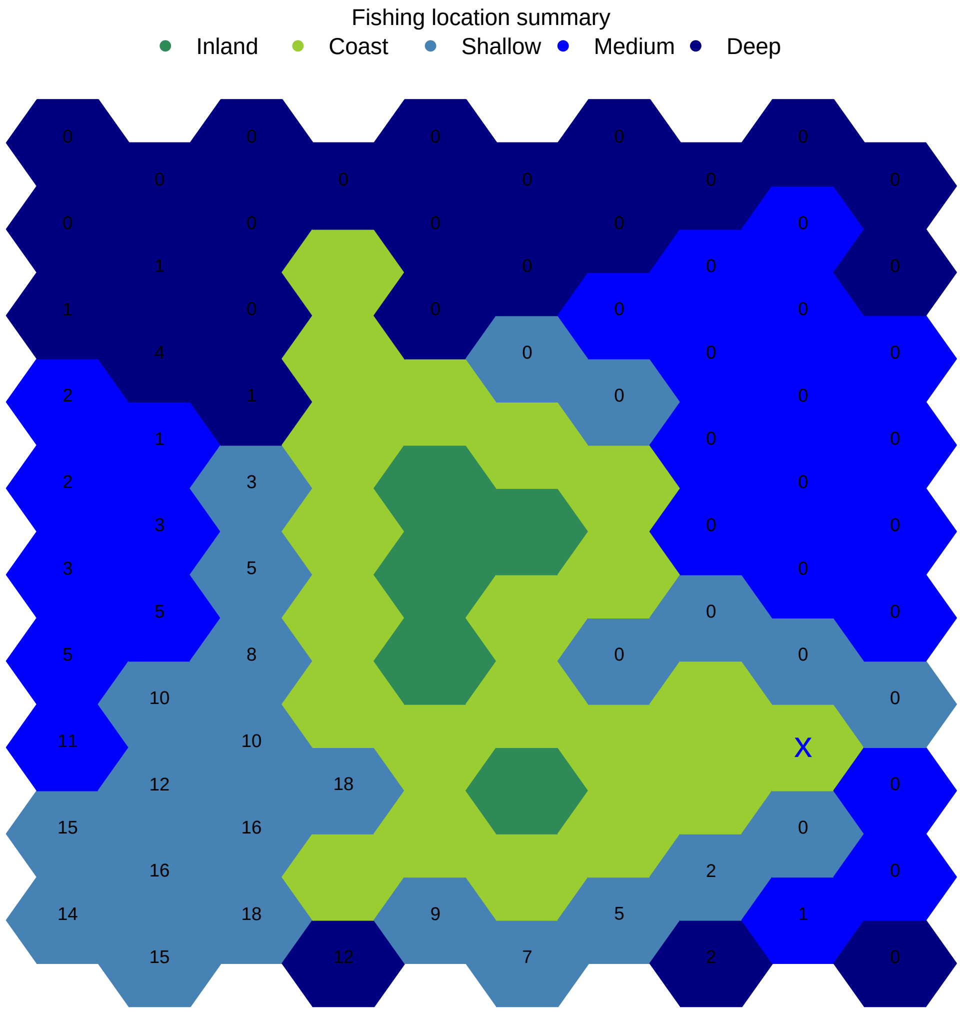


Figure 21.7: Summary of fishing locations used during the first iteration of the WPM case-study simulation. Numbers indicate the number of times each hex was used for fishing activity. The blue cross indicates the home port.

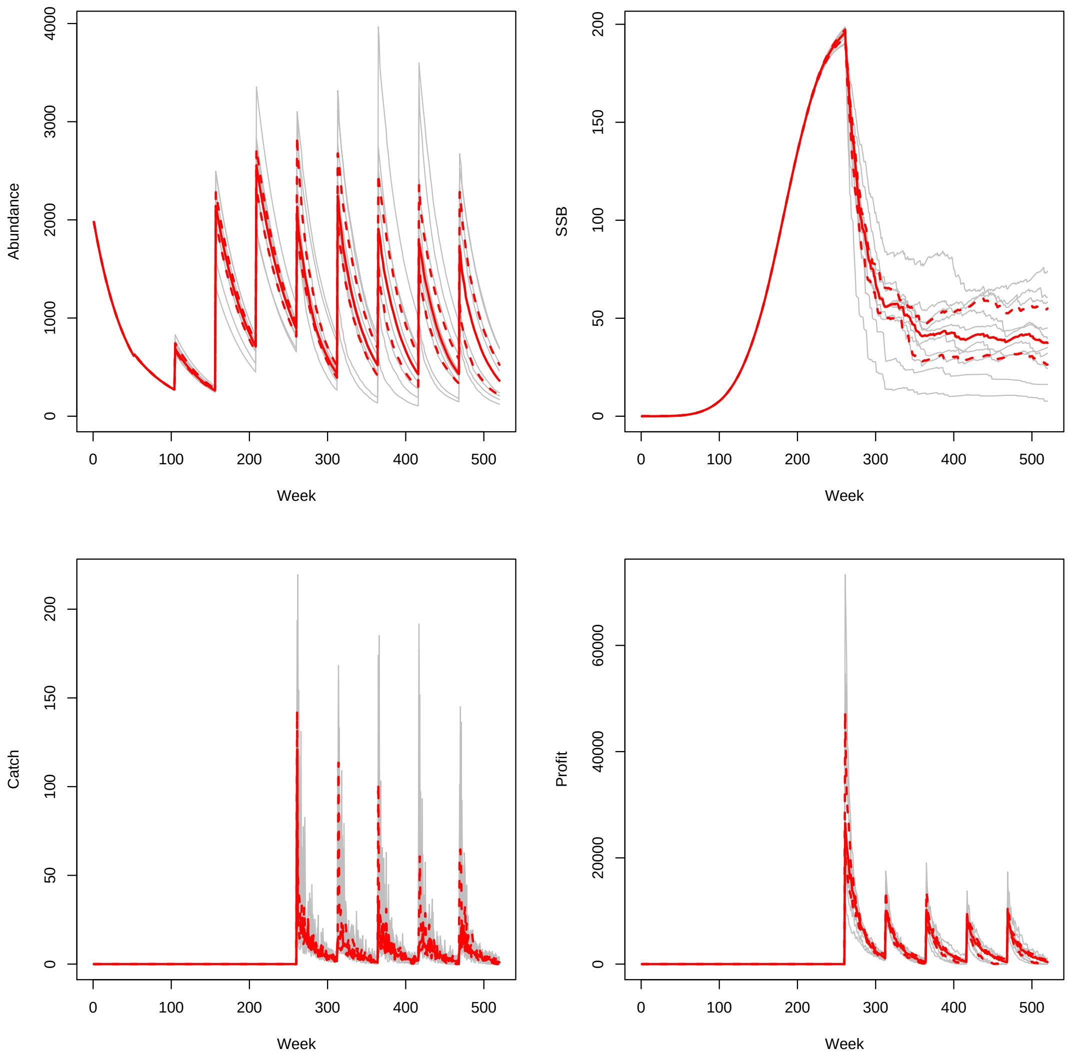


Figure 21.8: Comparison of weekly stock summaries for the 10 iterations of the WMP case-study simulation. Grey lines give the values for each iteration, while red lines give the 25th, 50th and 75th quantiles across all 10 iterations.

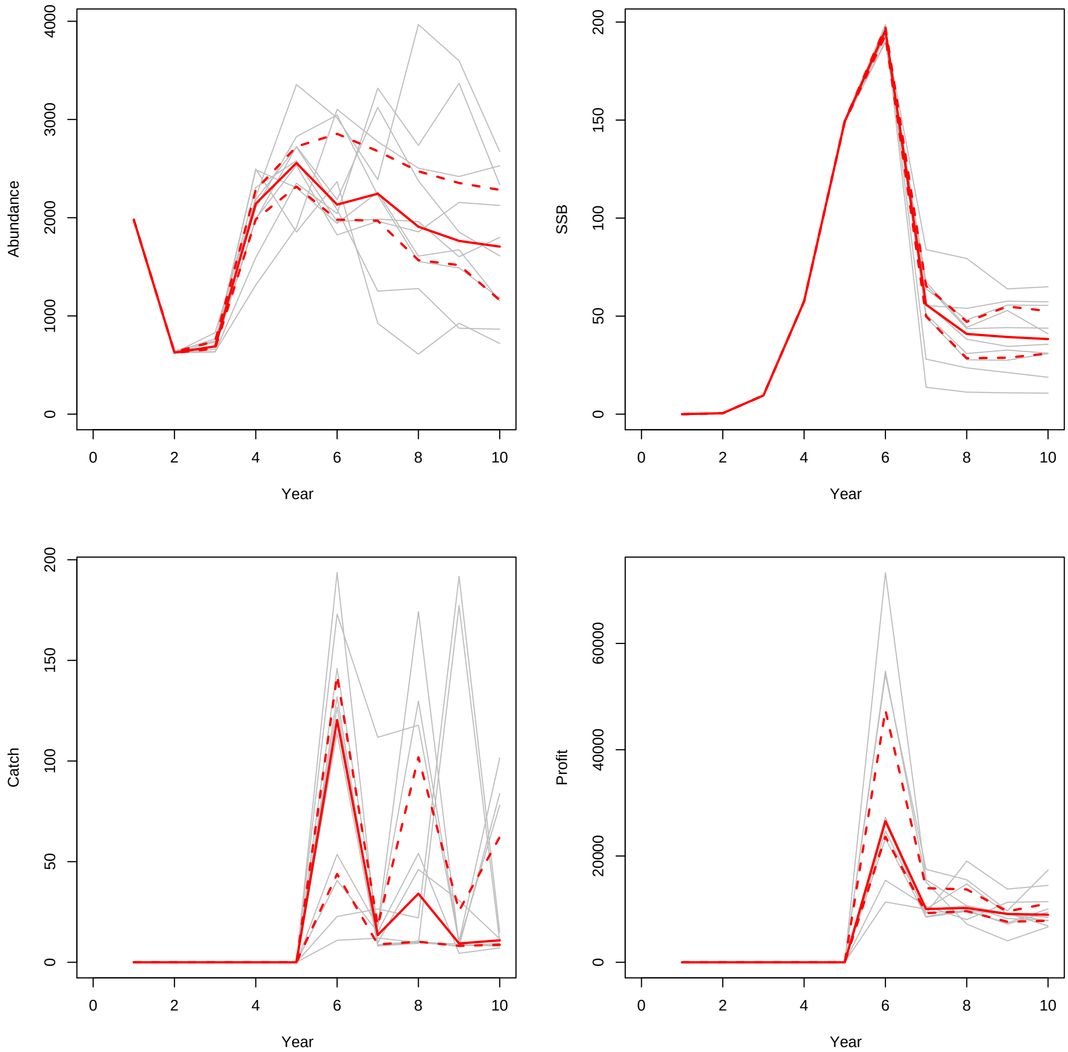


Figure 21.9: Comparison of annual stock summaries for the 10 iterations of the WMP case-study simulation. Grey lines give the values for each iteration, while red lines give the 25th, 50th and 75th quantiles across all 10 iterations.

21.3 Weekly catch quotas

In the second set of simulations, the vessel's task each week was to fish in the hex which maximised its catch (in weight), as long as said catch did not exceed 15 fish units (the weekly catch quota: note that I am not specific here about exactly what a "fish unit" is, as the unit used is not very relevant to the test analysis). Thus, when choosing the fished hex, all those hexes for which implied catch was greater than 15 fish units in that week were declared out of bounds. Profit was not a consideration in this approach, so it was possible for the vessel to make a loss in achieving its weekly catch quota.

Rather than include all of the diagnostics plots that were given for the first iteration of the WPM case-study simulation, I focus here for the first iteration of the WCQ case-study simulation on the weekly (Figure 21.10) and annual (Figure 21.11) stock summaries. These retain a degree of cyclicity in catch and profit, but both generally start lower than for the WPM simulation and decline less rapidly. This is to be expected: the vessel is limited in how much it can catch early in the year, so there are more fish left to catch later in the year. I also note that there is no underlying downwards trend in abundance, and that while SSB and TSB both decline after fishing starts, their stable levels are noticeably higher than for the WPM simulation. Again, it could be hypothesised that a lower but more consistent catch is more sustainable for a fishing business, but I will not attempt to address this directly here (except to suggest that the hex-model framework provides a useful tool for exploring such questions in the future).

Finally, Figures 21.12 and 21.13 present stock summaries for all 10 iterations of the WCQ case-study simulation. On average, SSB shows a tendency to increase after a nadir around week 300, and while catch is limited to be less than 15 fish units, it never drops away to zero either. Note also that some profit values become negative in these simulations.

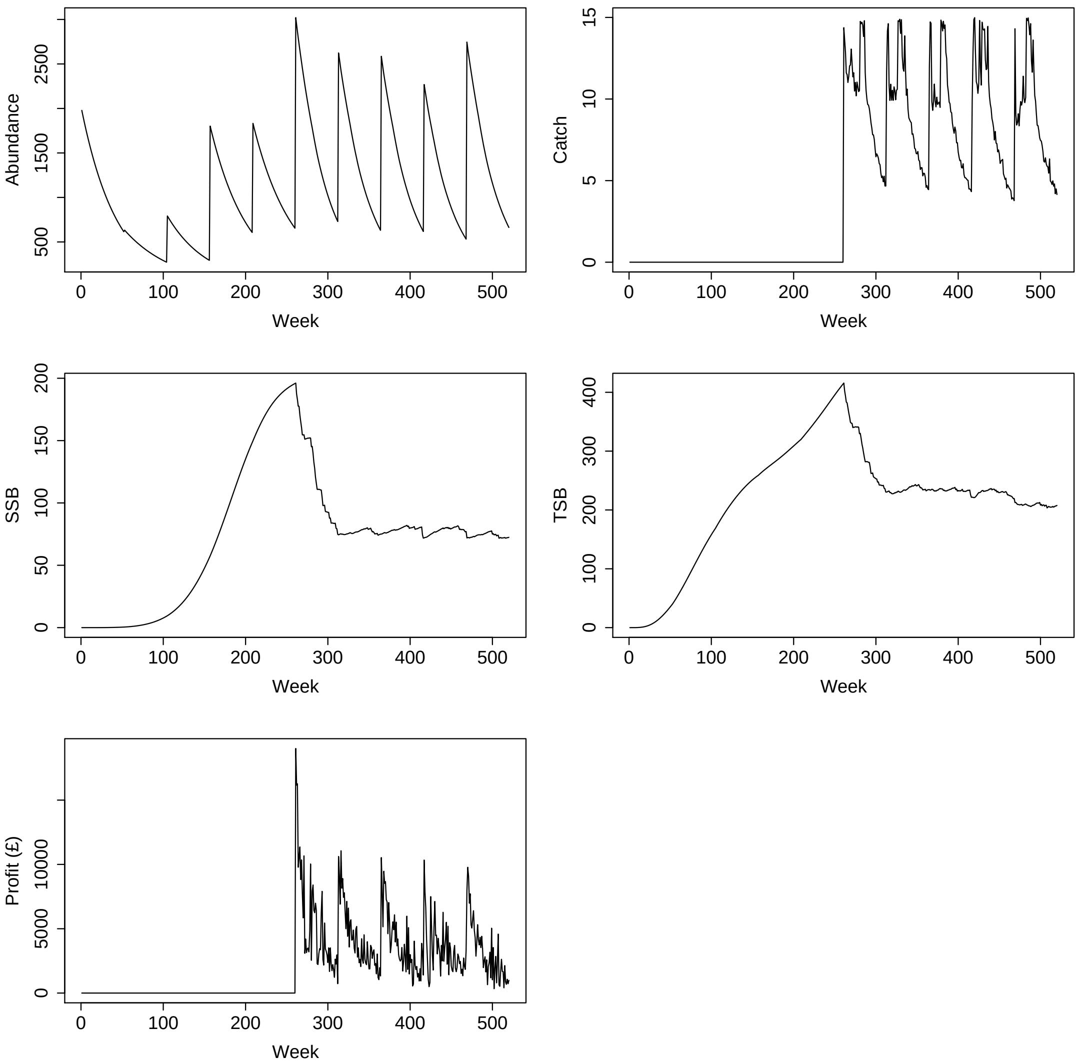


Figure 21.10: Weekly stock summaries for the first iteration of the WCQ case-study simulation.

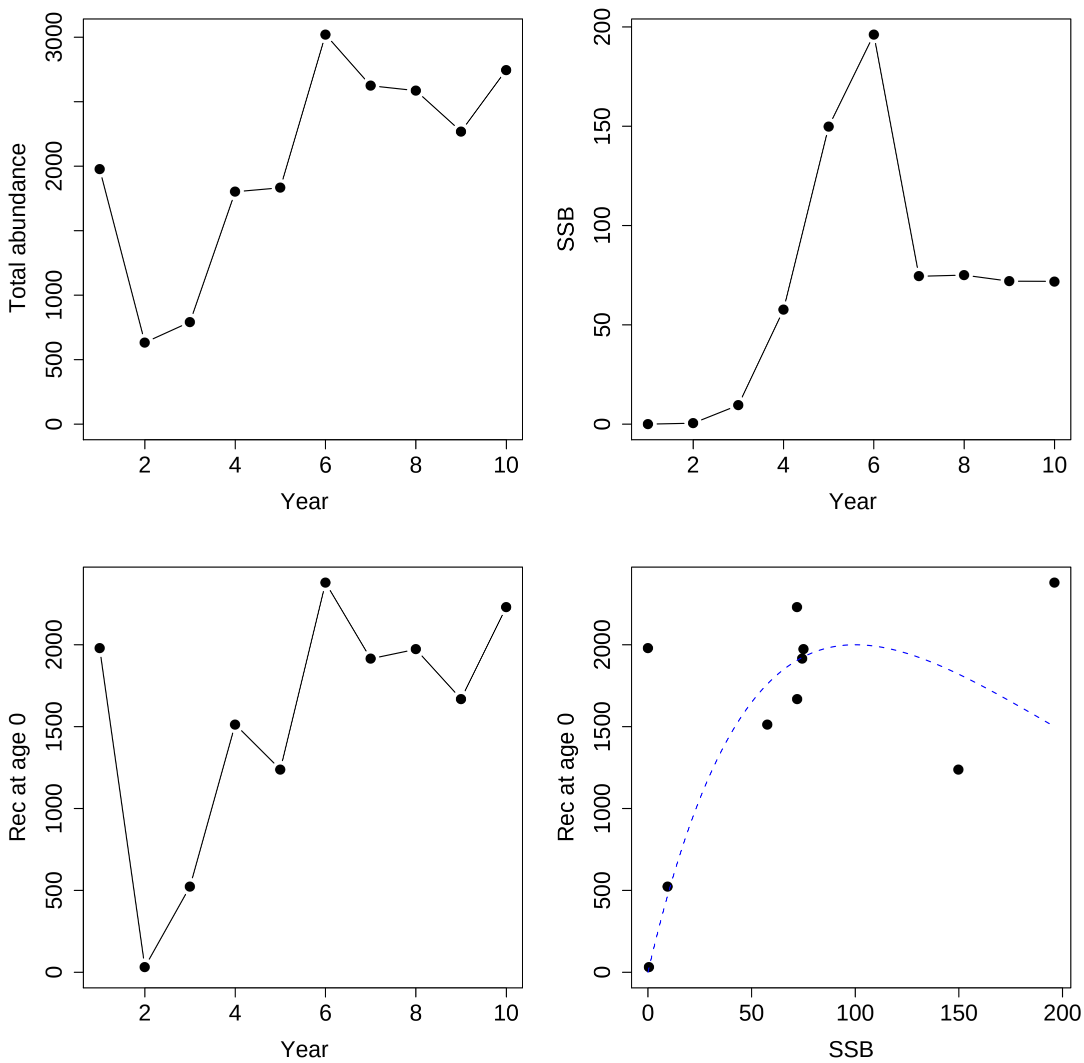


Figure 21.11: Annual stock summaries for the first iteration of the WCQ case-study simulation. The blue line on the stock-recruitment plot (lower right) is the underlying Ricker curve used to generate recruitment in the simulation.

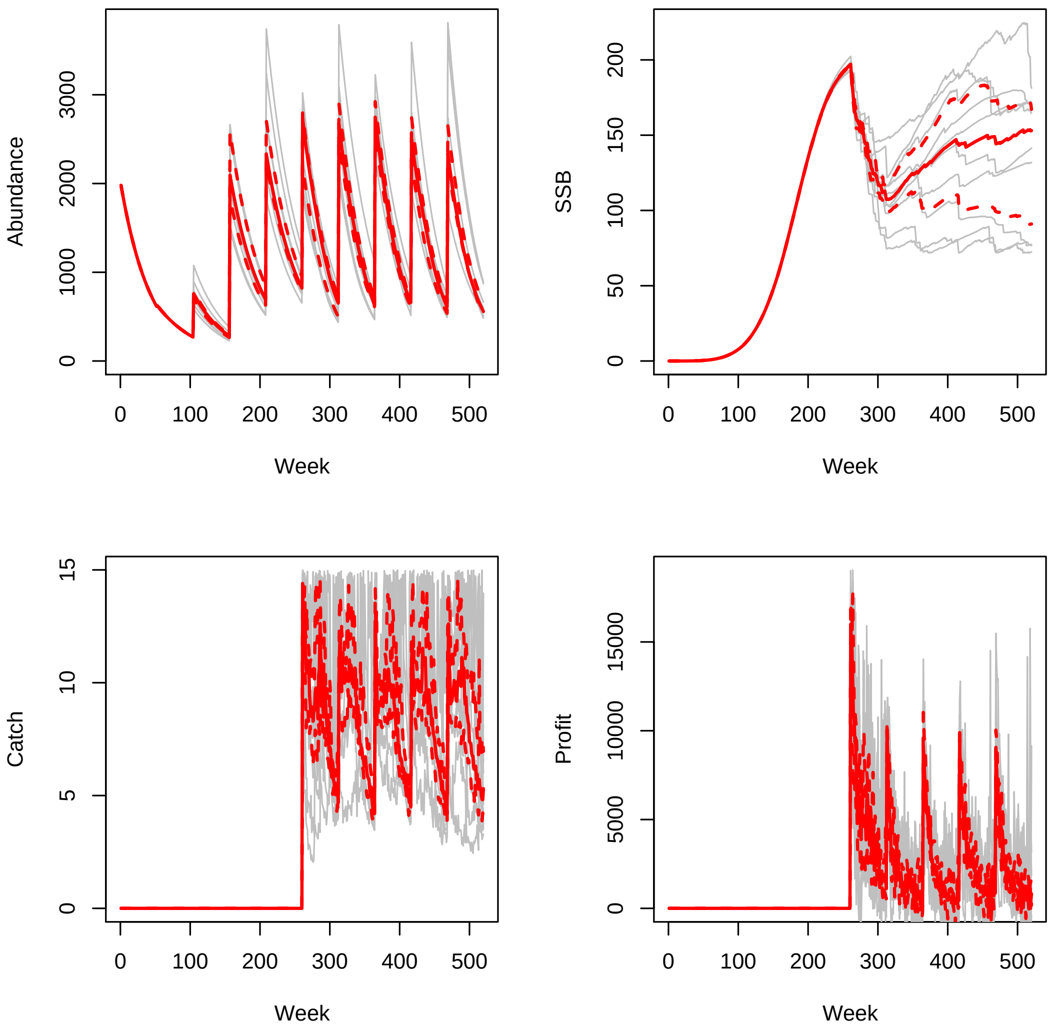


Figure 21.12: Comparison of weekly stock summaries for the 10 iterations of the WCQ case-study simulation. Grey lines give the values for each iteration, while red lines give the 25th, 50th and 75th quantiles across all 10 iterations.

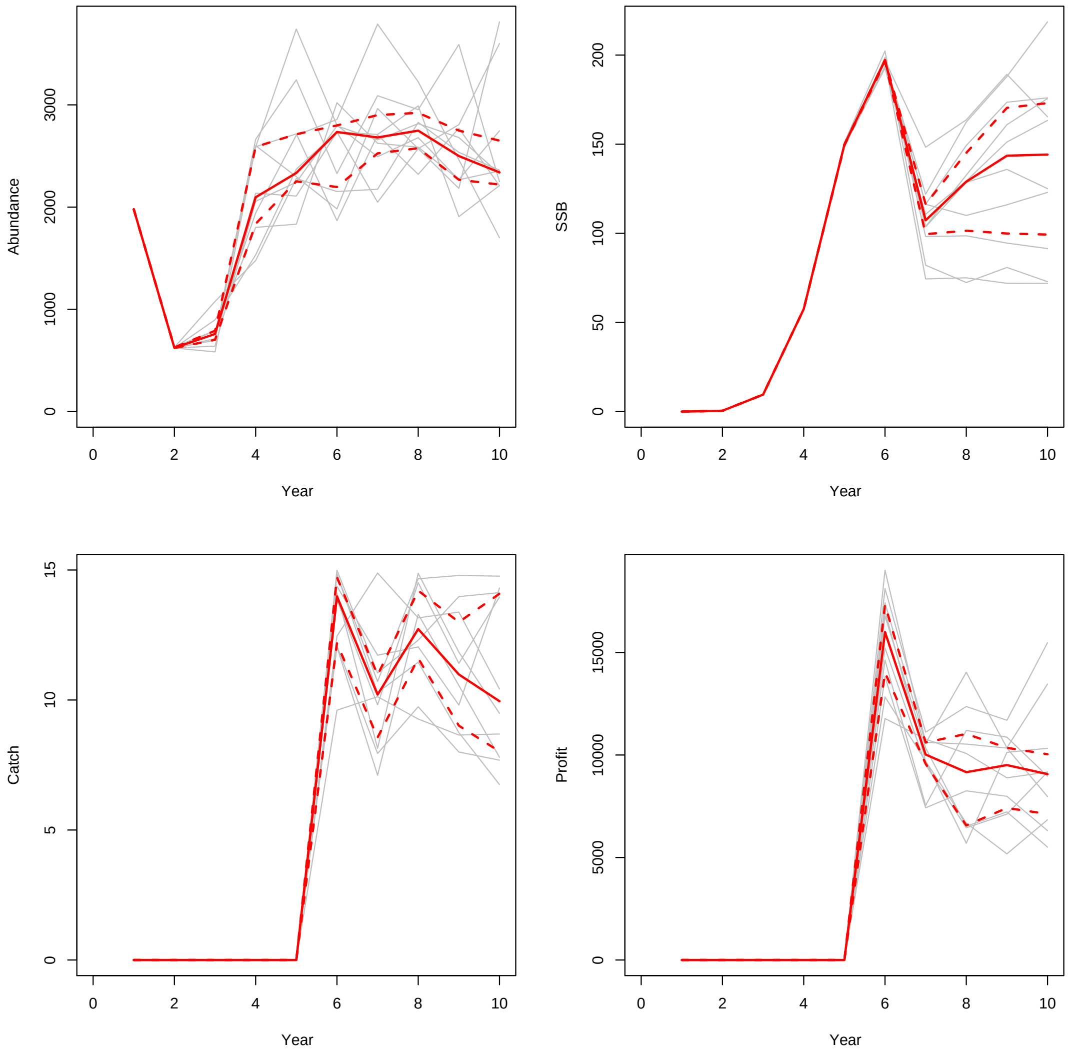


Figure 21.13: Comparison of annual stock summaries for the 10 iterations of the WCQ case-study simulation. Grey lines give the values for each iteration, while red lines give the 25th, 50th and 75th quantiles across all 10 iterations.

21.4 COMPARING WPM AND WCQ

The differences between the WPM and WCQ approaches are clear when comparing Figures 21.8 and 21.12. In the former (WPM), large catches and profits are possible, particular early in each year, but yields are very inconsistent and high profits decline rapidly. The cost of the profit-maximisation approach is also apparent in the low level of spawning-stock biomass in comparison with the unfished state. In the latter (WCQ), catches and profits both tend to be lower but are much more stable through each year, and the benefits can be seen in terms of a much higher stable level of spawning-stock biomass.

Table 21.1 provides a further comparison between the approaches, considering the mean and cumulative catches and profits, and the mean spawning-stock biomass. On average, catches are slightly higher for WPM, and profits are around a third higher, but at the cost of much lower biomass.

Although interesting, these results do not perhaps bear much relevance for any current fisheries management issues, as there are too few iterations to permit the drawing of robust conclusions, and the WCQ approach in particular is not particularly realistic: it is unlikely that a skipper would fish knowing he was losing money. However, the value of this short demonstration lies in the illustration of the potential of the hex-model simulation method for evaluating management plans and approaches. Both of the harvest-control rules considered in this Section were very easy to specify within the model, and comparing the effects of each is also straightforward. In the next Section, I consider a number of different ways of modifying and improving the model, and a number of different management approaches that would be amenable to evaluation using it.

	Approach	
	WPM	WCQ
Mean weekly catch	9.932	8.649
Cumulative catch for all years	2582.35	2248.61
Mean SSB	58.24	98.32
Mean weekly profit	£3897.24	£3030.95
Cumulative profit for all years	£1,013,282.13	£788,046.92

Table 21.1: Summary statistics from two fishery simulations using the hex model, and implementing two harvest-control rules: allowing the vessel to attempt to maximise weekly profit (WPM), and limiting weekly catch to 15 fish units or less (WCQ). Results are averaged over 10 iterations. See text for further details of simulations.

22 Future work

In this Section, I will list some of the developments in the hex model that would be both useful for improving it, and tractable to implement, along with management measures which could be evaluated using it. I have not attempted to rank these in importance or ease of implementation, but I note that anything that increases the complexity of the model very much should be treated with caution. Although somewhat intricate, and potentially complicated when using many hexes, vessels and stocks, the hex model is essentially a simple construct of a fishery system which will undoubtedly be much more complicated in reality. However, this is a benefit for application to real problems, and for interpretability of the outcomes, as simple models of complex processes can be more instructive than complex models (Hamre 2003, Paola 2011).

Optimised code The current R implementation of the hex-model algorithm does not run particularly quickly. The principal elements which will retard R code are loops and the overuse of data frames and/or lists (Anglim 2010, Thulin 2011). In developing a fast numerical parameter estimation function for the SURBAR survey-based asssessment method (see Section 8.3), I restructured the original Fortran-90 code to vectorise all loops, and converted all data frames and lists to numerical matrices. Doing so improved the speed of the algorithm by several orders of magnitude. For the hex model, there are several processes which take up a great deal system time in R, most notably the A* shortest path algorithm, and capacity or random diffusion of fish. During early development of the hex model, I wrote an implementation of the A* algorithm in Fortran-90 which could be called from R. I no longer have access to the Fortran-90 compiler with which to develop this further and the R implementation has been used in the meantime, but the time savings were quite impressive (Table 22.1). Alternatively, these problematic algorithms could be redeveloped in R as I did for SURBAR. This optimisation is probably as essential precursor to the serious use of the model to provide advice to fisheries managers, as it is currently too slow and unwieldy.

Uncertain information In the simulations presented in Section 21, I assumed that the skipper of the vessel could know precisely how many fish at each age the vessel would catch if it were to fish in any given hex. This meant that the fishing approach being used (WPM or WCQ, in this case) could be followed very closely: if weekly profit maximisation was the goal, the vessel could achieve that exactly. In reality, of course, fishing is more a matter of highly educated guesswork, and even the existence of a "skipper effect" determining fishing success has been widely debated (Hilborn

n_h	Fortran-90	R
10	0.02	1.17
20	0.04	1.44
30	0.06	0.93
40	0.27	12.94
50	0.52	4.31
100	30.88	94.01

Table 22.1: Comparison of runtimes (in seconds) for the A* algorithm in Fortran-90 and R. n_h is the number of hexes per side of the simulated area, while the results are the times it took for the algorithm to find the shortest distance between two randomly selected hexes. Only one path for each n_h was calculated, but it was the same path for Fortran-90 and R.

and Ledbetter 1985, Russel and Alexander 1996). Assuming this effect does exist, an experienced skipper will know where he is *likely* to get good yields of particular species at particular times of year (Thorlindsson 1994, Colding et al. 2000), but until the net is hauled back up he does not really *know* what he is going to catch. If this were not the case, then management measures to encourage (for example) cod avoidance in the North Sea would have been much more successful in recent years than they have been (ICES 2011c). The hex model therefore needs to be able to include uncertainty into how much each skipper knows about the stock distribution of the fish he is trying to catch. One possible approach to be explored is to fit gamma distributions to the age distribution in each hex, apply multivariate resampling (Needle and Hillary 2007) to the gamma parameters, and generate resampled age distributions which are similar to (but differ from) the true distributions and which the simulation would use in the location-decision process. Furthermore, management evaluations could be repeated for different levels of this uncertainty, to model the influence of skippers of varying levels of experience.

Uncertain management implementation What are the implications if there are discrepencies between what a manager thinks will happen, and what actually does happen? Instructive examples include North Sea haddock (Needle 2008c), for which there is a consistent underestimation of F in the MSE, caused by an inappropriate discard model; and Fraser River sockeye salmon (Holt and Peterman 2006), for which the value of F used in management and MSEs can be under- or overestimated, depending on current stock size. Spatio-temporal simulations such as the hex model would enable managers to evaluate whether this type of discrepancy is likely, and whether it is driven by fishing patterns.

Multiple vessels The case studies presented in Section 21 assumed that the fishery consisted of only one vessel, for parsimony and to ensure tractable run-times. However, the presence of vessels with different characteristics can have a significant effect on the success or otherwise of a management plan (Campbell and Dowling 2005, Bastardie et al. 2010), and as vessel data and settings are coded in the R software as a list, the simulations are readily extendible to two or more vessels. This would allow the model to be used to consider issues of competition for resources, and the classic "tragedy of the commons" problem (Hardin 1968, 1998). For example, the likelihood of success (or otherwise) of management measures such as quota points (see Section 7) could be evaluated. Approaches such as these are important examples of bottom-up, industry-driven management that may be more likely to succeed due to "reciprocity, reputation and trust" (Kraak 2011), yet without quantitative demonstration of possible outcomes it is difficult for many fisheries managers to believe that bottom-up control can ever work. Progress in this direction will require developments in the model to account for social cooperation in a multi-vessel simulation, so the question can be asked whether this leads to a better outcome than short-term self-interest? The *ecoOcean* gaming application of Nissen et al. (2011) has been used to demonstrate that "players" (that is, skippers) must cooperate in order to prevent overexploitation under standard quota-based management, and the hex model has the potential to demonstrate how likely this is in the real world away from games.

Multiple stocks Including more than one stock in the hex model would enable consideration of the effects of both mixed fisheries and multispecies predation. As for vessels, stock data and settings are stored as a list, so extending the simulation to several stocks would be straightforward. Hamre (2003) gives an example of a possible management approach accounting for multispecies predation in the Arctic (although the conclusion that mortality on immature cod should be *increased* in warm periods while capelin abundance is low would need very careful consideration before implementation), while the *Strathrecovery* model provides a more detailed and flexible approach for the North Sea (Guirey et al. 2008, Speirs et al. 2010). Pilling et al. (2008) did not model interspecific predation, but their study of a linked plaice-sole fishery in the southern North Sea was instrumental in the wider acceptance of a multistock management plan. Models of this type could readily be simulated in the hex model, with hex-based natural mortality dependent on the respective distributions of predator and prey species. The issue of mixed fisheries can be summarised by the question of whether vessels will switch targets to different species if economic conditions are right: in this context, the hex model provides an excellent method of evaluating developments in such management measures as quota points (see Section 7) which are essentially attempts to deal with the problems inherent in mixed fisheries.

Surveys In reality, fisheries stock assessments (and hence scientific advice to fisheries managers) are based on a combination of commercial catch data and research vessel survey indices. The reason for this is that catch data are based on a very large sample size, but may be biased by (for example) incomplete reporting or vessels aggregating, and hence these data generally have low variance but (potentially) high bias: on the other hand, survey data are derived from a relatively small sample, but should not have much bias, so *these* data have high variance but low bias (Beare et al. 2005). The intention behind using both sources is to try and generate an assessment with low variance and low bias. It would be straightforward to simulate a research-vessel survey in the hex model, using perhaps a low selectivity across all ages (so hence a high variance) and a regular grid of surveyed hexes (so hence a low bias). The generation of survey data would enable evaluation of survey-based assessment and advice (Section 8), and comparison with management approaches that rely on both catch and survey data, or just catch data.

Annual management decisions The current implementation has explored the effects of two very simple harvest-control rules (HCRs). The vessel attempts to maximise profit each week, or the vessel attempts to catch the highest yield that is less than 15 fish units (Section 21), but these HCRs do not include management intervention. Of more interest are the management strategies and HCRs used in reality, such as those for haddock evaluated in Chapter II. The single-species, non-spatial evaluations described in that Chapter were flawed to a certain extent because they could not account for changes in fleet dynamics. Real-life HCRs of this kind would be quite straightforward to implement in the hex model, and this would enable a more effective evaluation of the management plans used to set fishery quotas across the world.

Economic targets The hex model could include a requirement that vessels fish through the year to achieve weekly profits lying on some predetermined *profit curve*. Suitable shapes for this could include constant through the year, high towards Christmas, high early in the year when fishing is often good on gadoid spawning grounds, and so on. The hex model also has the potential to be used to explore neoclassical economic theories of resource utilisation (e.g. Clark 1976) to see if they hold under realistic simulations of fleet dynamics.

Discards No allowance has yet been made for the fact that fishermen (unless prohibited from doing so) will discard fish which they do not wish to land, either because they have no quota for them, they are too small to be landed legally, or the current market price would make landing uneconomic (see Section 4). The spatio-temporal economic hex model could be used to address and and attempt to understand this problem, once restrictive quotas, gear selectivity and fish-distribution uncertainty are built in, and further to understand to potential effects of discard bans.

Closed areas In Chapter III I considered the likely effects of closed areas in European waters, and concluded that short-lived real-time closures mostly served to attract vessels towards cod: or at least, higher cod abundance led to increases in both closures and fishing effort, so the former could not be considered to be a strong control on the latter. Further afield, short-term closures have been used in the Bering Sea to reduce bycatch of non-target species such as chinook salmon and Pacific halibut (e.g. Haflinger and Gruver 2010). More permanent closures have been used in a number of Californian rockfish fisheries (National Oceanic and Atmospheric Administration 2011), and in New England to reduce exploitation rates on demersal species such as cod (New England Fishery Management Council 2007). Many fisheries managers have imposed permanently-closed areas (Marine Protected Areas, or MPAs) as a means to protect sensitive habitats and increase the local abundance and diversity of ages of targeted stocks (Claudet 2011). There is also often an underlying assumption that closures will have beneficial effects for populations as a whole. However, work to date (Hilborn et al. 2006, Walters et al. 2007, see also Chapter III above) has suggested that closed areas, in themselves, may not necessarily lead to the benefits that managers expect. Effort displaced by closures moves to other areas, and the negative effects of the increased effort in other areas may offset the benefits to the closed areas. The case studies in Section 21 did not consider this aspect, but closing an area for three weeks (say) in the hex model would be very easy. Indeed, it would be straightforward to simulate the full range of measures in the Scottish Conservation Credits scheme (see details and references on page 141). The hex model could then be used to ascertain whether the effect I demonstrated for Scottish vessels fishing for cod is universal, and if not, under what circumstances one might expect a real-time closure scheme to be successful.

Length and size structure As discussed on page 244, the draft version of the hex model was based on fish *length* distributions, rather than the age distributions used in the implementation presented in this thesis. As many processes affecting fish are controlled by length (or size), rather than age, it would be appropriate at some stage to move to a length-based simulation approach, using methods such as the size-transition model of Gurney et al. (2007) or the combined length-age model (CALA) of Martin and Cook (1990). Switching to length-based modelling would also facilitate the inclusion of more biological realism (see, for example, Persson et al. 2007, Walters et al. 2007, Leeuwen et al. 2008) and evaluations of length-based assessment and advisory methods (Pauly and Morgan 1987).

Chapter V

Conclusions

When I am teaching courses in stock assessment to postgraduate students (Needle 2009b), fisheries science colleagues (Needle 2008e, Needle 2009a), or active fishermen, I often use a simple analogy to explain why stock assessment is so hard. Imagine (I will say) that you are in a hot-air balloon, flying high over a strange land completely hidden by a thick layer of cloud. You have been asked to write a report on this land – what lives there, how many of each species there are, how they reproduce, how the populations might change in the future – a complete ecosystem summary, in fact. And you have been given a basket and a long rope. So you lower your basket, scrape it along the ground for half-an-hour or so, haul it up, and have a look at the contents. Then you repeat the exercise a few times, although you are limited in how often you can do this by the amount of burner fuel you have. And then you have a look at what you have dragged up, and try and write your report. But, inevitably, you will have missed large swathes of land. You might be scraping at a time of the year (or hour of the day) when many species are hiding in holes. Your basket would have got stuck if you had scraped through towns, so you won't have caught many people at all. And you will have missed the land's teeming bird population altogether. So your ability to estimate the abundance of any particular type of animal is reduced by the fact that you can't see them, and by the tools available to you to sample them.

Now think about the biology and behaviour of the fish themselves. Forestry scientists tell us that their estimates of the number of trees in a wood are accurate to within 20%, roughly (G. Clarke, University of Aberdeen, *pers. comm.*). But trees are stationary, and tree reproduction is limited more by space than anything else. It is far more challenging to estimate fish numbers, when they can move quickly from place to place, and when the numbers of young fish are determined by a whole range of factors from the numbers of adult fish, to the numbers of predators or prey there are, to the way the wind happened to be blowing on a particular day.

So these are some of the challenges that stock assessment scientists face. But, relatively speaking, the assessment of historical events is the easy part. It is much more difficult to predict what is likely to happen in the future, yet this is what is required for management strategy evaluation. The difficulties in forecasting fish recruitment (and hence future fish population dynamics) have been widely covered in the literature (see a review in Needle 2002), but the development of an understanding of how fishermen might change their actions in response to management measures (imposed or otherwise) has progressed much more slowly. In the words of Holt and Peterman (2006): errors in the implementation of management strategies occur "in part because managers are unable to predict exactly the behaviour of harvesters in response to regulations and therefore usually can not take this behaviour into account when setting regulations."

I first realised the importance (and serious implications) of this propensity when producing the evaluation of the EU-Norway management plan presented here in Section 4, and published in Needle (2008c) amongst other papers. My model included a knowledge production module, in which virtual landings, discards and survey data were generated on the basis of fish abundance from an underlying biological population module. These data were passed into the same stock assessment model as used in the real ICES assessment (ICES 2011c), and management decisions were taken (in the management implementation module) that were based on the stock abundance and mortality estimates produced by this assessment model. In each simulation run, I would know the true underlying abundance (and hence spawning stock biomass B) *and* the values of B returned by the assessment model. Unfortunately, the latter were always lower than the former, often by a considerable margin, which meant that my virtual "managers" would be taking decisions based on underestimates of biomass and would therefore act more harshly than truly warrented. This was not, then, a truly unbiased evaluation of the management plan.

But why did this effect arise? I spent days trying to fix it, exhaustively changing parameters in the assessment model, modifying survey data, and adjusting the clauses of the management plan itself. Eventually it occurred to me that the main problem was an inadequate model of discarding, when allied with a low target F and a constraint on interannual variation in TAC. Following common practice and in the absence of information that would have helped me to do otherwise, I had assumed that discard proportions-at-age were fixed through time. When a large year-class appears, in the context of a low target F and a constraint on how much TAC can increase interannually, the actual response of the real fishery would be to increase discarding, on the large year-class in particular, since the increase in TAC would necessarily lag behind that of abundance. However, my model did not account for this: adequate models of discard behaviour were not yet well-developed (and still are not).

This is the crux of the problem. Fisheries scientists are asked by fisheries managers to pronounce on whether proposed management plans are likely to provide sustainable fisheries for the foreseeable future, with all the ecological, economic and social benefits this would bring. Since the number of young fish that recruit to the adult population is one of the great imponderables of fisheries science (Needle 2002), scientists do not claim to know what recruitment will be, but rather implement simulation models which evaluate the likely risk inherent in the application of the management plan over a randomly-generated range of plausible future recruitment levels. They then report the risk as the probability that biomass will be below some reference point in ten years' time, or the number of years over the next twenty years that this can be expected to happen, and managers are satisfied that a transparent and justifiable scientific process has supported the use of their management plan. But the scientists have had to make a number of simplifying assumptions in their model, and one of the principal tenets is that fishing practices will not change in response to management measures. We therefore fall into the classic trap of assuming something that is patently untrue in order to make our models work, and then omit to advertise the fact widely.

Some authors (e.g. Rochet and Rice 2009) have concluded that quantitative management strategy evaluation is not to be trusted, and have advocated other, more qualitative approaches, such as learning from past application of management plans (including comparison across areas and biota). This thesis is part of an effort to take the other path. I contend here that these alternative approaches present even more problems than quantitative MSEs, and that the issue is how to *improve* the latter. Specifically, I have tried to consider in some detail the problems of changing fishing practices (and hence fleet dynamics) raised by the case studies in Sections 4 to 6, and to think about how these problems might be addressed by a different approach to management strategy evaluation.

Of course, there are much wider issues that I could have considered here as well, to do with management strategies themselves (rather than just their evaluation). Around half-way through my doctorate I had defined four key questions that I thought the thesis should address, all concerned with information and uncertainty and how these affect fisheries managers. I raised these in Chapter I with a promise to return to them, so here they are:

1. How does the robustness of different assessment management approaches depend on sources of uncertainty?
2. What is the smallest amount of information on which successful fisheries management can be based?
3. What must fisheries managers know?
4. What are the important sources of error and uncertainty?

For example, consider a simple age-based forecast system such as that caricatured in Figure 22.1. What is important in this system is dependent (most directly) on the type of management being carried out and the type of fishery. Examples include:

- If the abundance N_{y+2} in the quota year is the metric (that is, the thing that management decisions are based on), and if the fishery operates mainly on young fish with a high F, then the appropriate forecasting of recruitment is crucial. In this case, neither abundance N_{y-1} nor growth are very important.

- If the metric is N_{y+2}, the fishery operates on older fish, and R_{y-1} is large (a strong year-class), then the final-year assessment of N_{y-1} is what will drive management.

- If spawning-stock biomass B_{y+2} is the metric, then management will be driven by the N_{y-1} estimates and by forecast growth models. In this case recruitment forecasts are relatively unimportant, as few of the recruits will contribute to B_{y+2}.

So I had a list of important questions that needed to be addressed. Following the principle that complex realities are best understood through simplified simulations (Harte 1988, Paola 2011), I decided to implement a generic fishery model (initially known as the "lake" model, but subsequently referred to here as the hex model) to act as a test-tube for exploration of hypotheses. But I quickly ran into difficulties. Firstly, although simplified, the hex model still had to be able to "represent" reality to a certain extent, and this proved to be a strenuous undertaking. Secondly, before I could consider the effect of uncertainty on fisheries managers, I needed to be able to characterise (and hence simulate) the likely response of fishing fleets to decisions that managers would take: otherwise I would be back at my starting point of trying to evaluate a management plan without considering changes in fleet dynamics. It quickly became clear that there was a wealth of preparatory work to be done before the key questions laid out in Chapter I and above could be answered, and it is this work on which this thesis has focussed. The questions themselves remain largely unanswered for now, but I would argue that I am in a much better position to consider addressing them in the near future.

This thesis consists of three main Chapters. In Chapter II (*Motivating case studies*), I considered a number of analyses that I used to stimulate the work in the remainder of the thesis. The first of these were three evaluations of management plans for haddock (*Melanogrammus aeglefinus*) in the North Sea (ICES Divisions IVa, IVb, IVc and IIIa; Section 4), West of Scotland (ICES Division VIa; Section 5) and Rockall (ICES Division VIb; Section 6); a map is given in Figure 4.1. I demonstrated, using relatively simple age-structured, non-spatial MSE models, that while all three of these MSEs suggested that the management plans concerned would be sustainable over the medium- to long-term, they were all hindered by a poor understanding of fish discarding practices which made the applications of the plans more restrictive than would have been the case in reality. The MSE for the West of Scotland compounded this

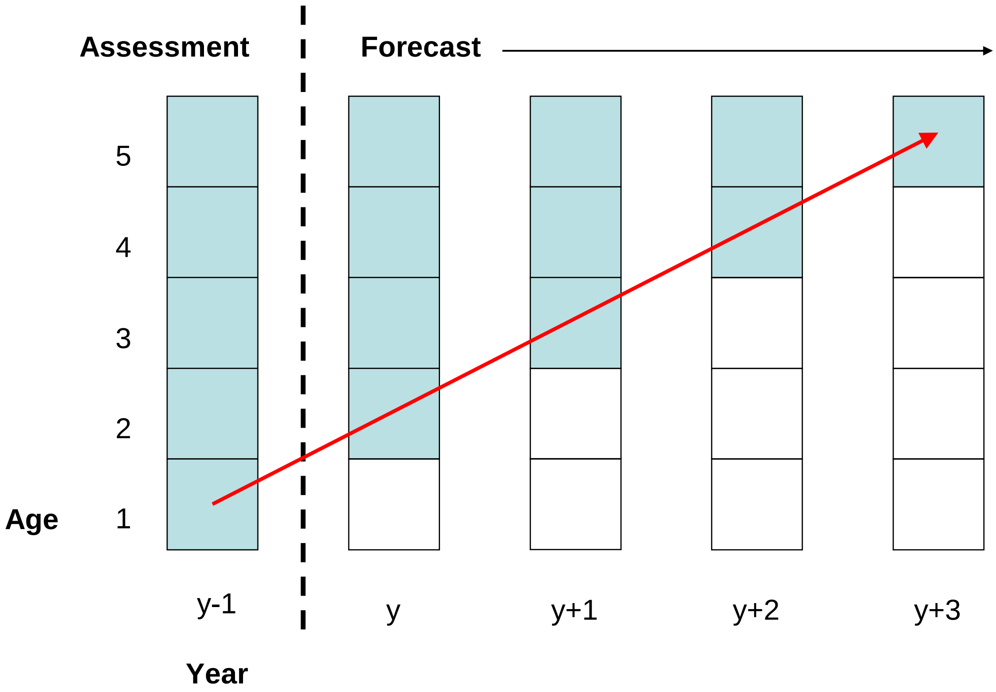


Figure 22.1: Caricature of a simple age-based forecast system. Shaded cells indicate abundance forecasts that are determined (to a greater or lesser extent) by the final-year $(y-1)$ assessment. Unshaded cells are determined by recruitment forecasts. The red arrow shows the progress of the $y-2$ year-class. y is the assessment year, $y+1$ is the quota year.

difficulty by splitting catches into landings, discards *and* unallocated removals: here, discards are poorly understood, but unallocated removals are not understood at all. The Rockall haddock MSE improved one aspect of the previous MSEs, in that the use of newly-available FLR evaluation functions enabled a much wider exploration of the confidence intervals about the results, but the underlying problem with fleet dynamics and discard practices remained. In none of these evaluations was I able to characterise (and hence model) the likely *response* of the fishing fleet to the management measures that the evaluations were trying to appraise.

This is a problem of some concern, as the MSEs could fairly be said to be inadequate yet the management plans in question are either being used by managers, or are under serious consideration for future use. The North Sea haddock management plan has been used by the European Union and Norway to set quotas for that stock since 2005 (ICES 2011c). The status of the West of Scotland management plan is currently somewhat unclear. The version of the plan in which the TAC constraints only applied when $B > B_{\mathrm{pa}}$ (see Needle 2010a, and Section 5) was reviewed by ICES and passed as being sustainable (Section 5.3.3.1 in ICES 2010a). A modification was subsequently requested by the European Commission, for which I provided a further evaluation (Needle 2010b). This was apparently mislaid by ICES and was not formally reviewed, so the management plan remains in abeyance. Following a meeting of the EU-Russia Working Group on Rockall haddock in Moscow in September 2011, the Rockall haddock management plan is in the process of being further modified and will be reconsidered in 2012.

Chapter II concluded with short summaries of work on quota points (Section 7) and survey-based assessment models (Section 8). Both of these aspects would readily lend themselves to evaluation using the kind of system developed later in the thesis. Previous evaluation approaches did not permit ready consideration of quota points as they are not (generally) multispecies in nature, and cannot simulate the switching between target stocks that is a likely response to discard bans and multispecies quotas. Similarly, survey-based assessment methods have been difficult to evaluate before because previous methods have not been able to account for such inherently spatial aspects as the catchability discrepancy caused by the mismatch between survey distributions (which are expected to cover the entire area) and fishery distributions (which would only cover the stock areas in which it is profitable to fish). I focussed on these two issues in Sections 7 and 8 because I have studied them both in some detail in recent years, but I would suggest that the applicability of the spatio-temporal fisheries model presented in Chapter IV to the evaluation of measures such as closed areas, closed seasons and gear restrictions is clear. While time has not allowed me yet to consider these aspects in the framework of the hex model, the groundwork is in place to enable me to do so in the very near future.

In Chapter III (*Characterising fleet dynamics*), I looked in depth at the response of the Scottish demersal fishing fleet to the imposition of a system of real-time closures (RTCs), starting in 2008 and expanding to the present day. RTCs had been imposed by the Scottish Government in an effort to reduce the mortality exerted by this fleet on the North Sea cod stock, and thereby save the fleet from the full brunt of stringent effort penalties imposed by the European Commission on countries who could not demonstrate a reduction in cod mortality. The immediate question was whether a movement of vessels away from RTCs (and hence, away from areas of high cod abundance) could be shown with available data. The deeper question, and the one of more relevance to the thesis, was whether this fleet exhibited a characteristic response to such closures that the hex simulation model would need to be able to reproduce in the fullness of time. If the fleet ignored RTCs, then the model could too, but if the fleet could be shown to move either towards or away from RTCs, then the model would need to be able to replicate that behaviour (probably as an emergent property) if it was to be applicable to evaluations of RTC-based management.

The Chapter began with work on the development of a Relative Fish Importance Index (RFII), which was intended to avoid the obvious hyperaggregation pitfalls inherent in using landings data to infer fish distributions. In other words: fishing vessels will probably go where the most profitable fishing areas are, so landings data (even assuming they are reliable) tell us little about the full stock distribution. I then considered aspects of data from the fishing industry which have only been made available to scientists within the last few years, namely VMS data (for which I discussed sources, collation and public dissemination) and CCTV data from Remote Electronic Monitoring or REM (which I used to provide a simple ground-truthing result on the widely-held assumption that trawlers must be travelling at less than 5 knots to be able to fish). The combination of fish distributions (from the RFII) and vessel-specific fishing locations (from VMS and CCTV data) enabled a detailed analysis of the response of Scottish vessels to RTCs.

I did this in two ways. Firstly, in Section 13, I identified all those trips which fell into one or more of three categories: fishing in the area of an RTC in the 15 days before closure (denoted *before*), fishing in an RTC during closure (*during*), and fishing in the area of an RTC in the 15 days after reopening (*after*). These were the trips that I deemed to be affected by the RTCs, for the purposes of this analysis at least. For each such trip, I calculated the average RFII for all the VMS fishing pings in the trip, and compared that with the average RFII for the "comparison trip" (for *before* and *during* trips, the comparison was with the following trip: for *after* trips, it was with the preceding trip). I measured the distance between the geographic medians of the trip and the comparison trip. These two metrics enabled me to determine whether the vessel moved to an area of less cod abundance when moving away from an RTC, or towards an RTC, and how far the vessel moved on each occasion. I also applied a standard t-test to decide whether RFII differences between trips were statistically different to zero.

My conclusion from this first analysis, when applied to all relevant vessels during 2008-2010, was as follows. There is significant evidence for a decreased RFII for cod when vessels move away from newly-implemented RTCs (*before*), but the reduction in RFII for cod is at least matched by an equal and opposite *increase* in RFII for cod when vessels return to RTCs after reopening (*after*), for the year as a whole and for all quarters. There are differences in the detail between the years, but this overall pattern appears to be maintained. These results suggest that RTCs encourage vessels to move away from cod-important areas when they are closed, but do not necessarily discourage renewed fishing on cod when they are reopened.

In the second analysis, in Section 14, I considered what the effect of RTCs might have been on *all* vessels in the fleet to which RTC legislation could reasonably be expected to apply: in other words, not just those vessels fishing in or around each RTC in the same broad period as the closure. The question was then: could I detect any significant change in patterns of fishing locations from year to year (within each quarter), and could those changes be linked to changes in the numbers of RTCs in or around those fishing locations?

To address these questions, I first limited the full Scottish VMS dataset to those vessels which had VMS data records for every year, and which had appropriate catch compositions, gear types and fishing locations. For each of the resulting 188 vessels (54% of the total), I applied a specifically-designed cluster analysis procedure to generate estimated discrete fishing areas for the vessel. Then, considering each quarter separately, I used a randomisation approach to determine whether the distribution of VMS pings for a vessel over its fishing areas changed significantly from year to year. I also calculated the change over the years in the numbers of RTCs within each fishing area, by quarter and vessel. Finally, for those vessels, quarters and years for which the change in VMS distribution was deemed significant, I collated contingency tables to tally the fishing areas for which VMS pings decreased, stayed the same, or increased, and for which RTC numbers decreased, stayed the same, or increased.

There were generally too few observations to reach statistically significant conclusions for any one vessel when considered individually, but when the data were collated across the full fleet the results were quite strong. I showed that changes in the RTC count do have a significant effect on changes in VMS ping counts, and furthermore that the direction of the relationship is *positive*. That is: an increase in the numbers of RTCs in fishing areas is linked to an increase in fishing activity in those areas. Both analyses therefore reached the same conclusion: that real-time closures of the limited duration used by Scotland in the North Sea do not in themselves lead directly to cod avoidance, and may indeed have the opposite effect. As a Scottish fishery scientist in an advisory role, I find this a valuable (if rather disappointing) result, but in the context of the hex model, it stands as an excellent example of fleet dynamics that the model would need to be able to replicate.

Having presented several case studies of MSEs in Chapter II, and characterised particular responses of the Scottish whitefish fleet to management measures in Chapter III, I turned to the development and partial testing of the final spatio-temporal fishery ("hex") model in Chapter IV. In each run of the model, the simulation area is built up from hexes representing land areas or different sea depths. The sea hexes are populated by fish of one or more species, following species-specific rules on spawning and recruitment, growth, diffusion and movement, carrying capacity, and natural mortality. The population in each hex is represented by a distribution at age to which all processes are applied (so the model is not based on the individual, but on groups of individuals), and the principal time-step is weekly. After an initial burn-in period to allow the populations to develop, one or more fishing vessels commence activity from their designated home port, with each vessel having specified selectivity characteristics. The only income available to the vessel is the value of the fish they catch (as determined by an age-based price curve), while their only cost is that of travelling through hexes (the A* algorithm is used to ensure the vessels take the shortest possible route for each trip).

I presented two simple examples of how this model might be used, each allowing for one fish stock and one vessel, and assuming that the vessel had perfect knowledge of the stock distribution in each hex. In the first example, the vessel was assumed to be trying to maximise profit (income minus costs) for each week and would select the hex to fish in accordingly. In the second, the aim was to maximise catch under a specified upper catch limit. Although the simulations were limited by time constraints to only ten iterations each, the results indicated that the profit maximiser would make more money over the five-year simulation period and have a slightly higher average catch than the catch-quota vessel, but that the profit and catch would both fluctuate much more for the former than for the latter. I also showed that the average level of spawning-stock biomass when the profit-maximising approach was applied was around half that for when the catch-quota approach was used.

These simple case-study simulations were perhaps not very useful in themselves, but they did serve an important function in testing the hex model, and indicating the range of possible management approaches which it could be used to evaluate. In the remainder of Chapter IV (and to conclude the main body of the thesis) I outlined some possible future developments in the hex model that would be both useful for improving it, and relatively easy to implement, along with management measures which could be evaluated using it. These include the need to optimise the code for speed; methods to account for uncertainty in information provided to vessels and managers, or discrepancies between what managers think will happen when they impose measures and what actually happens in the fishery; testing the inclusion of multiple vessels and multiple stocks; the simulation of research-vessel surveys; the evaluation of more complicated management plans such as are used in reality; and a number of other methodological issues to do with economic targets, discards, closed areas, and length-based data structures.

To conclude: I have presented several motivational case studies to highlight the need for an improved spatio-temporal fishery modelling framework. I have characterised the response of the Scottish whitefish fleet to real-time closures, as an example of the type of fleet dynamics that a new model would need to be able to simulate. Finally, I have developed, implemented and tested a new simulation model which I would argue is flexible and powerful enough to enable insightful quantitative analysis and evaluation of the wide range of management approaches that will be required. This work is certainly not yet complete, but over the period of this doctorate I have progressed it considerably in the right direction, and I feel confident that I and my advisory colleagues will be in a much better position to advise fisheries managers on stock sustainability well into the future.

Chapter VI

Published papers

This Chapter presents facsimiles of two published papers (Needle 2008c, Needle and Catarino 2011) on which parts of this thesis have been based, along with a related poster (Needle 2007a). Permission to reproduce Needle (2008c) has been granted by Elsevier BV (`www.elsevier.com`). Permission to reproduce Needle and Catarino (2011) has been granted by Oxford University Press (`www.oxfordjournals.org`).

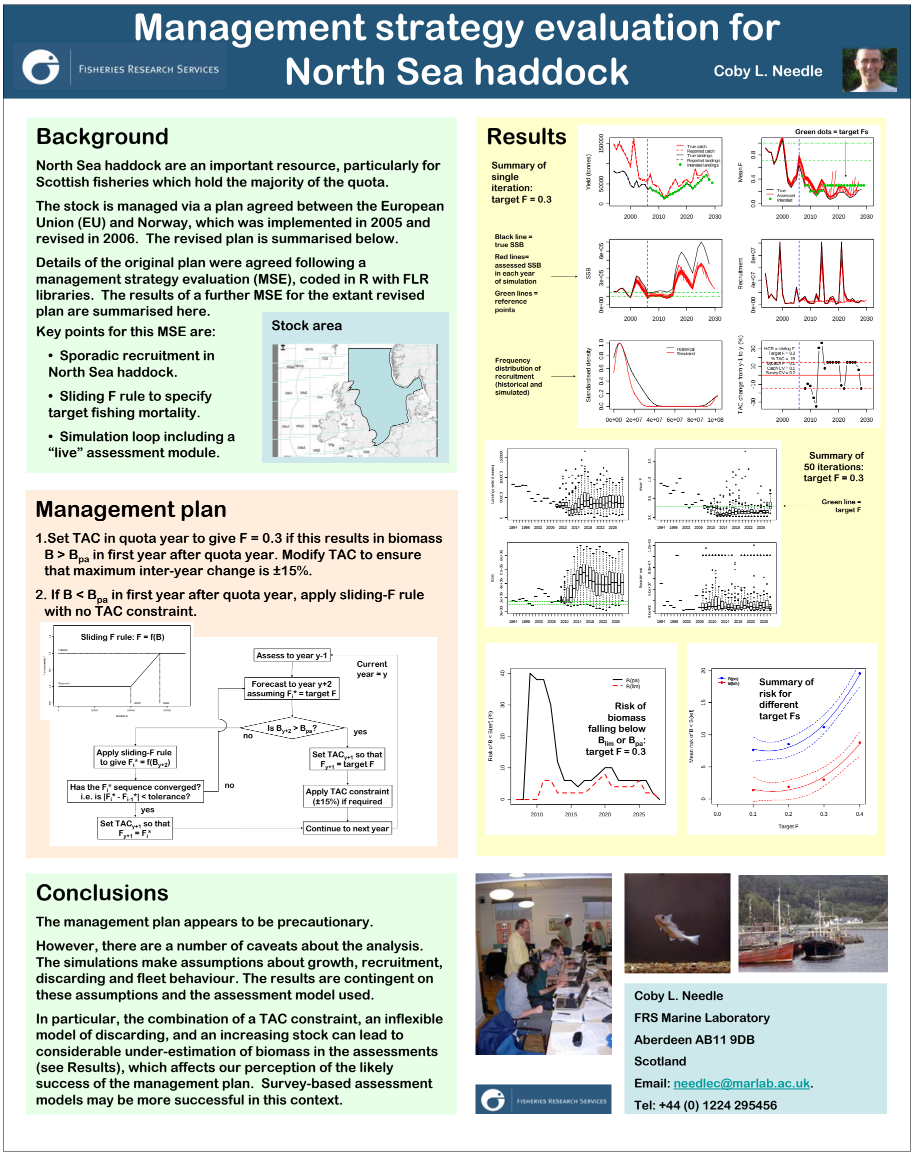


Figure 22.2: Poster presented at the UNH Haddock 2007 Symposium, held during 25-26 October in Portsmouth NH, USA.

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Management strategy evaluation for North Sea haddock

Coby L. Needle *

FRS Marine Laboratory, PO Box 101, 375 Victoria Road, Aberdeen AB11 9DB, Scotland, United Kingdom

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ABSTRACT

North Sea haddock (*Melanogrammus aeglefinus*) are managed under a plan agreed between the European Union (EU) and Norway. This management plan was reviewed during 2006. As part of the review process, a quantitative management strategy evaluation (MSE) was undertaken, both of the existing plan and of proposed modifications. The evaluation was implemented in the R programming system, using FLR libraries, and was based on stochastic simulations of the complete fishery system (including a biological operating model, a knowledge production model with "live" stock assessments, and a simple implementation model). The generation of appropriate time-series of recruitment was of key importance for a stock like North Sea haddock which produces sporadic large year-classes. Although some refinement of growth and discard models is still required, tentative conclusions can be reached on the likely efficacy of different management plans. Well-defined MSEs have the potential to impart useful information for assessment scientists, fisheries managers and stakeholders.

1. Introduction

In many parts of the world, agreements exist between different nations that allow their fishermen to participate in shared international fisheries. Some of these shared fisheries are also subject to shared management, in which governments meet to agree on how to regulate fishing effort, and how much effort to allow. A yet smaller subset of fisheries is subject to international fisheries management plans and harvest control rules, which seek to automate the management response to perceptions of stock dynamics (and reduce the need for the long negotiations that can accompany the utilisation of any shared resource). For managers to be able to devolve much of their negotiating power, they must be confident that management plans will deliver what they expect (Kell et al., 2006a); and in order to do this, plans must be tested. This can rarely be done at sea, so management strategy evaluation (MSE) is usually conducted via computer simulation (Cooke, 1999). In this paper I discuss such an MSE for North Sea haddock, or more specifically, haddock in Sub-Area IV and Division IIIa (Fig. 1) of the International Council for the Exploration of the Seas (ICES).

This stock is exploited both by European Union (EU) member states and by Norway, and is managed as a shared stock. In 1999 the EU and Norway agreed the terms of a management plan for haddock, which was finally implemented in January 2005. The plan contained a clause specifying that a review was to be carried out by the end of 2006. In April of that year, the EU and Norway approached ICES to inquire about the feasibility of addressing this review through ICES assessment Working Group channels. It was agreed that the ICES Working Group for the Assessment of Demersal Stocks in the North Sea and Skagerrak (WGNSSK) would carry out the evaluation of the existing plan and any proposed modifications, and that the review would be prepared subsequently during the October 2006 meeting of the ICES Advisory Committee for Fisheries Management (ACFM).

Initial analyses (Needle, 2006a) were presented in June 2006 at the ICES Working Group on Methods of Fish Stock Assessment (ICES, 2006b), at which improvements and modifications were suggested. Consultations with managers and stakeholders followed, and updated results (Needle, 2006b) were discussed at the October meeting of ACFM (ICES, 2006a). The new analyses formed the basis of ICES advice to the EU and Norway which was presented at their annual bilateral meetings in November. In the margins of these meetings further discussions were held on the likely sustainability of the proposed plan, and this led to modifications (the addition of a sliding-*F* rule, which we discuss below, and the clarification of the time when biomass should be measured).

Following this process, the revised plan came into force on 1st January 2007. The text of the plan is reproduced in Appendix A. In essence, it can be simplified to two key points:

F_{target} and TAC constraint Set the Total Allowable Catch (TAC) in the quota year (that is, the year after the assessment) to give F_{target} = 0.3, where F_{target} is the intended mean fishing mortality over some

* Tel.: +44 1224 295456.
E-mail address: needlec@marlab.ac.uk.

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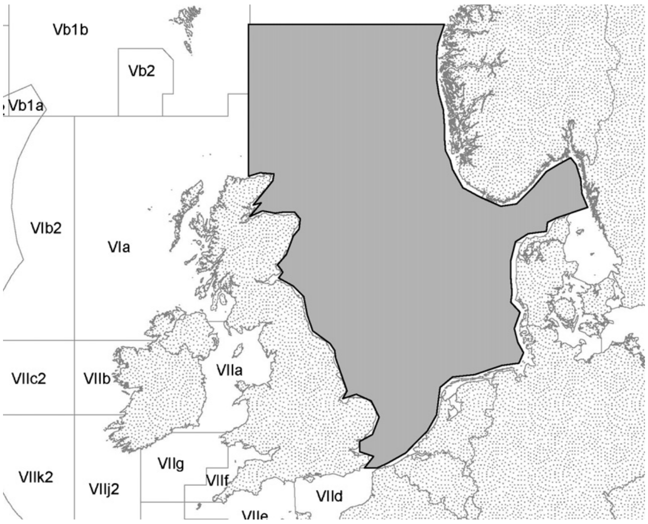

Fig. 1. The management area for North Sea haddock, consisting of ICES Sub-Area IV and Division IIIa (Skagerrak). Note that the Skagerrak is the northern part only of Division IIIa.

pre-specified age range (2–4 for haddock), as long as this results in spawning-stock biomass $B > B_{pa}$ at the beginning of the first year after the quota year. B_{pa} is defined as the precautionary level of biomass below which the stock should not fall. Modify the TAC to ensure that the maximum inter-annual change in TAC is ±15%. Note that, although "catch" is referred to in the plan, it is really landings that are controlled.

Sliding-F rule If, following the application of the $F_{target} = 0.3$ above, $B < B_{pa}$ in the first year after the quota year, apply the sliding-*F* rule with no TAC constraint (Fig. 2).

The procedure is laid out schematically in Fig. 3. The plan can be categorised as an *F*-based harvest control rule, in which F_{target} for a particular year is specified by the expected biomass that would be

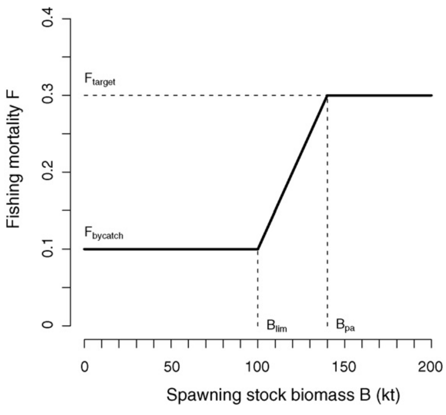

Fig. 2. The sliding-*F* rule (thick line) for specifying the intended fishing mortality rate $\tilde{F}$, based on the expected spawning-stock biomass *B* remaining after the corresponding quota has been taken. For North Sea haddock: $F_{target} = 0.3$, $F_{bycatch} = 0.1$, $B_{lim} = 100$ kt and $B_{pa} = 140$ kt.

left in the stock after the application of that F_{target}. The plan is also restricted to the use of quotas (rather than effort limits or technical measures) as the main management tool, although there is a vague reference to alternative approaches (Appendix A, clause 6).

The principal changes from the first (January 2005) version of the plan are the inclusion of the sliding-*F* rule, and the clarification of when biomass should be measured. The former is intended to prevent a strict adherence to a pre-defined F_{target} in situations where it is clearly no longer appropriate; the latter ensures that management decisions are based on predictions of the *results* of management actions. However, these two features make evaluation of the plan quite complicated. It is easy to envisage a situation in which the forecast at $F_{target} = 0.3$ leads to a biomass after the quota year which is between B_{lim} and B_{pa}. In this case the sliding-*F* rule stipulates a different F_{target} (Fig. 2), so the forecast must be performed again – which leads to another different F_{target}, and so on. This cycle converges to a single solution, but only at the cost of computational complexity and long run-times.

Fig. 3 shows an additional step in the simulated plan that is not present in the actual plan, namely the limit of interannual change in F_{target} to $\Delta F = \pm 25\%$. This must be included to prevent the rapid (and irreversible) increase in F_{target} that can occur when managers try to maintain quotas in the face of a long series of low recruitments. Although essential to prevent simulation failure, in practice it is seldom needed.

In this paper, I will present a method for evaluating the North Sea haddock management plan, along with a number of indicative results. I also draw conclusions on the likely sustainability of the stock under the plan, and highlight a number of limitations in the method which must be borne in mind when interpreting the results. Two of these are related to key features of the implementation. Firstly, haddock are sporadic spawners, and as such will tend to produce very large (but infrequent) year-classes, the sizes of which seem to be, to all intents and purposes, unrelated to parental spawning stock biomass. It is important, therefore, that the biological simulations on which the evaluations are based represent adequately this characteristic of haddock recruitment. Even if this is ensured, recruitment forecasting is still problematic, and this is

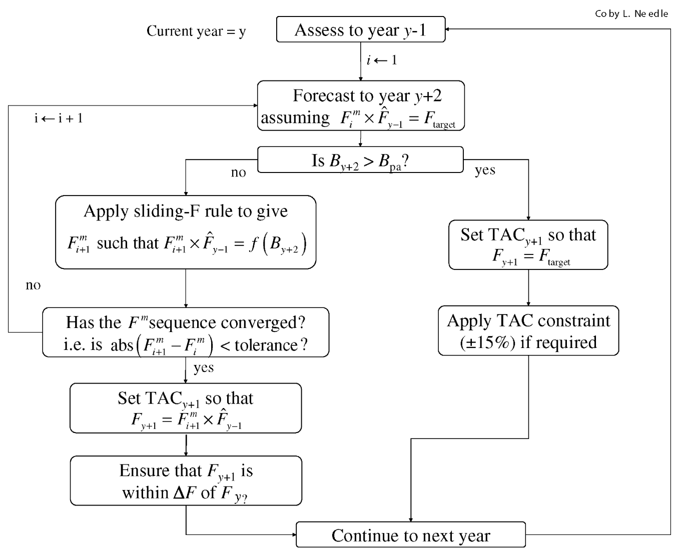

Fig. 3. Flowchart outlining the key points of the North Sea haddock management plan. See Appendix B for notation. Note that $f(B_{y+2})$ is shorthand for "the sliding-F rule applied to biomass in the year $y + 2$".

why many possible time-series of future recruitments are considered in any MSE. Secondly, management perceptions about a stock are largely driven by the assessments provided by fisheries scientists, so that the quality of management is largely a function of the quality of the assessment. The utility of any management plan is therefore dependent on the accuracy of the stock assessment. In order to evaluate fully a management plan, it is important that the evaluation includes a "live" stock assessment module as part of the simulation loop. The implementation presented in this paper does so, and allows us to observe the effects (sometimes deleterious, sometimes beneficial) of biased or noisy data and stock assessments on the success of management plans.

2. Methods

The basis of the management-plan evaluation code is the FLR package (FLR Team, 2006; Kell et al., 2007), a collection of data types and methods written in the R language (R Development Core Team, 2005) as part of the EU EFIMAS-COMMIT-FISBOAT project cluster (e.g. EFIMAS, 2007). Specifically, the code makes use of FLR data types for fish stocks, as well as stock assessment methods implemented in FLR, and expands considerably upon these to address the particular issues relevant to the North Sea haddock case study. Model parameters were defined on the basis of historical data, and then a number of simulations of future stock dynamics and fisheries management were performed. Fifty iterations were carried out for each of five different target fishing mortalities ($F_{\text{target}} = 0.1, 0.2, 0.3, 0.4, 0.5$), with each simulation running for 20 years into the future. Each F_{target} was evaluated in terms of the number of years in each simulation in which spawning-stock biomass B was below biomass reference points B_{lim} (considered an absolute lower limit) and B_{pa}.

The model algorithm can be summarised in brief as follows (a full description is given in Appendix B):

(1) Historical assessment data are read in, using ICES (2007) as the source. Run parameters are determined by an initial stock assessment; these include variables governing recruitment, discarding behaviour, fishery selectivity, and survey catchability.
(2) A biological simulation is carried out for the year in question. This generates recruitment, growth, and mortality, and results in values for abundance and biomass. In the first year, fishing mortality is assumed to be equal to a three-year historical average: in subsequent simulation years, fishing mortality or yield is determined by application of management decisions from previous years (with some implementation error).
(3) A stock assessment and associated short-term forecast are carried out, based on data up to (but not including) the current year.
(4) Management decisions for the following year are then determined, using information from the assessment and forecast and following the specified management plan to generate an intended landings yield.
(5) Steps 2–5 are repeated for the number of years required in the simulation.
(6) Finally, steps 2–5 are repeated for the number of iterations required (50 are used in this paper). Each iteration differs only in the time-series of generated recruitments, and in measurement error for landings and survey indices (although this error is of a much lower order than the recruitment variability).

A key requirement for applying the model to North Sea haddock is to ensure that it encapsulates adequately the sporadic nature of recruitment for the stock. Historically, North Sea haddock recruitment has followed a pattern of occasional large year-classes (the size of which seems unrelated to parental stock size, at least directly), interspersed with years of low-to-moderate recruitment (Fig. 4). In the model, this pattern is replicated by stipulating one large recruitment (of the order of the 1999 year-class; around 100 thousand million fish) in a random year within each 10-year simulation period. As the simulations are 20 years long, there will therefore be exactly two large year-classes within each iteration; this seems to be consistent with historical observa-

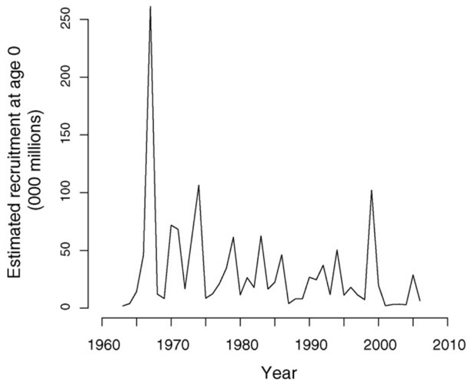

Fig. 4. Estimated historical time-series of recruitment at age 0 for North Sea haddock.

tions. A further proviso is to ensure that the large year-classes are separated by at least two years, as a potentially cannibalistic species such as haddock have never been observed to produce two large year-classes in succession. Recruitment for the remaining years in the simulation is given by a lognormal distribution about the geometric mean of the 10 years prior to 2006, not including 1999 (around 10 thousand million fish). Details of implementation of the recruitment model are given in Appendix B.

The modelling of discarding of haddock from the commercial North Sea fishery is also important for the effective simulation of the fishery and its management. However, this is a much more difficult issue to address successfully, as discarding behaviour is a function not only of stock abundance, but also of prices, costs, quota constraints, gear regulations, fishing distribution, and the availability of other fishing opportunities (amongst other factors). I have not attempted to model discards in this way in this paper, but rather have used fixed proportions of discarding at each age throughout the simulations (see Fig. 5). Specifically, the proportion

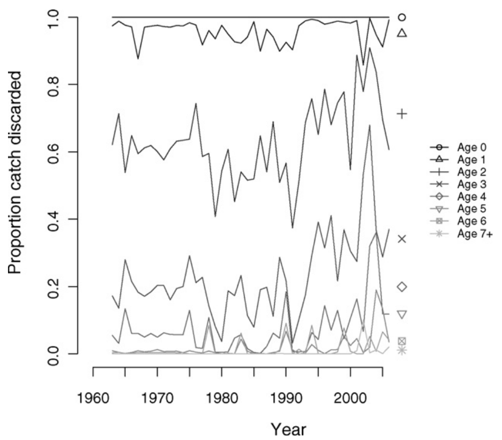

Fig. 5. Estimated historical time-series of discards at ages 0–7+ for North Sea haddock. The lines give the proportion of total catch for each age that was discarded. The points to the far right show the three-year average discard proportions for each age that were taken forward into simulations.

discarded at age a in the simulations is the mean of the proportions discarded at age a for the years $\gamma - 3$ to $\gamma - 1$ (here γ denotes the first assessment year, which is 2007 for this case study). This is an approximation that is unavoidable for now, that does have implications for the evaluation (see below), and that needs to be revisited during future work.

3. Results

Figs. 6–8 summarise the results of the analysis, which took around 75 h to complete due to the large number of repeated iterations and minimisations required to simulate such aspects as the TAC constraint and the sliding-F rule (Appendix B). As described above, the sliding-F iteration converged successfully on every occasion it was used.

Fig. 6 summarises the model output for a single iteration for $F_{\text{target}} = 0.3$ (50 such iterations comprised the full analysis for a particular F_{target}). In this iteration, the effect of the ±15% TAC constraint is clear in the time-series of intended landings (that is, quota or TAC; see Fig. 6a). Following the sliding-F rule, the interannual change in TAC deviates from the ±15% limits only for five years between 2018 and 2025 (Fig. 6f), which correspond to years for which *assessed* biomass falls below B_{pa} (Fig. 6c). However, in these years (and, indeed, in most years in the simulation), the true biomass was much higher, and this reveals the effect of the problem with discard modelling that was mentioned above. As fishing mortality is maintained at a low level, biomass begins to rise; but the TAC constraint means that landings do not rise commensurately. In reality this would probably lead to increased discarding across all ages, all else being equal, but that cannot happen in this model for which fixed proportions discarded at each age have been stipulated. For this reason, the catch (landings plus discards) on which the assessment is based is lower than it should be, and hence the assessed biomass is lower.

The data from the simulated survey series does not have this bias, but the assessment model used (FLXSA, an implementation of XSA) is largely driven by catch data with surveys playing a calibrative role (Darby and Flatman, 1994). Extensive testing during model development showed that none of the FLXSA settings (shrinkage and so on) could ameliorate the effect. A higher F_{target} or the removal of the TAC constraint do reduce the problem: however, these are not part of the plan under evaluation. The under-estimation also has consequences for fishing mortality, which is mostly estimated to be higher than it really is. The result is a management plan which is actually more conservative than it needs to be.

We note also that TAC increases of greater than 15% are possible (Fig. 6f). This will happen when a low assessment of spawning-stock biomass is combined with a large incoming year-class. The management plan operates on the basis of spawning-stock biomass, which remains low while the fish are young, so the constraint on interannual TAC variation does not apply. At the same time, the abundant young fish contribute to a higher quota forecast. The TAC must therefore increase by more than 15% if the management plan is to be followed. This result seems contradictory in a situation of low biomass, but is inevitable if the management plan is implemented as written.

The 50 iterations carried out with target $F_{\text{target}} = 0.3$ are summarised in Fig. 7. The median values from these plots are the result of smoothing across different realisations of recruitments, and are therefore useful only as an *indication* of likely future events. We note that the median outcome itself is not at all likely, given that each recruitment time series always has two large year-classes which are not reflected in the median. Median landings yield falls to a low level as the 1999 year-class is exhausted, before rising to a

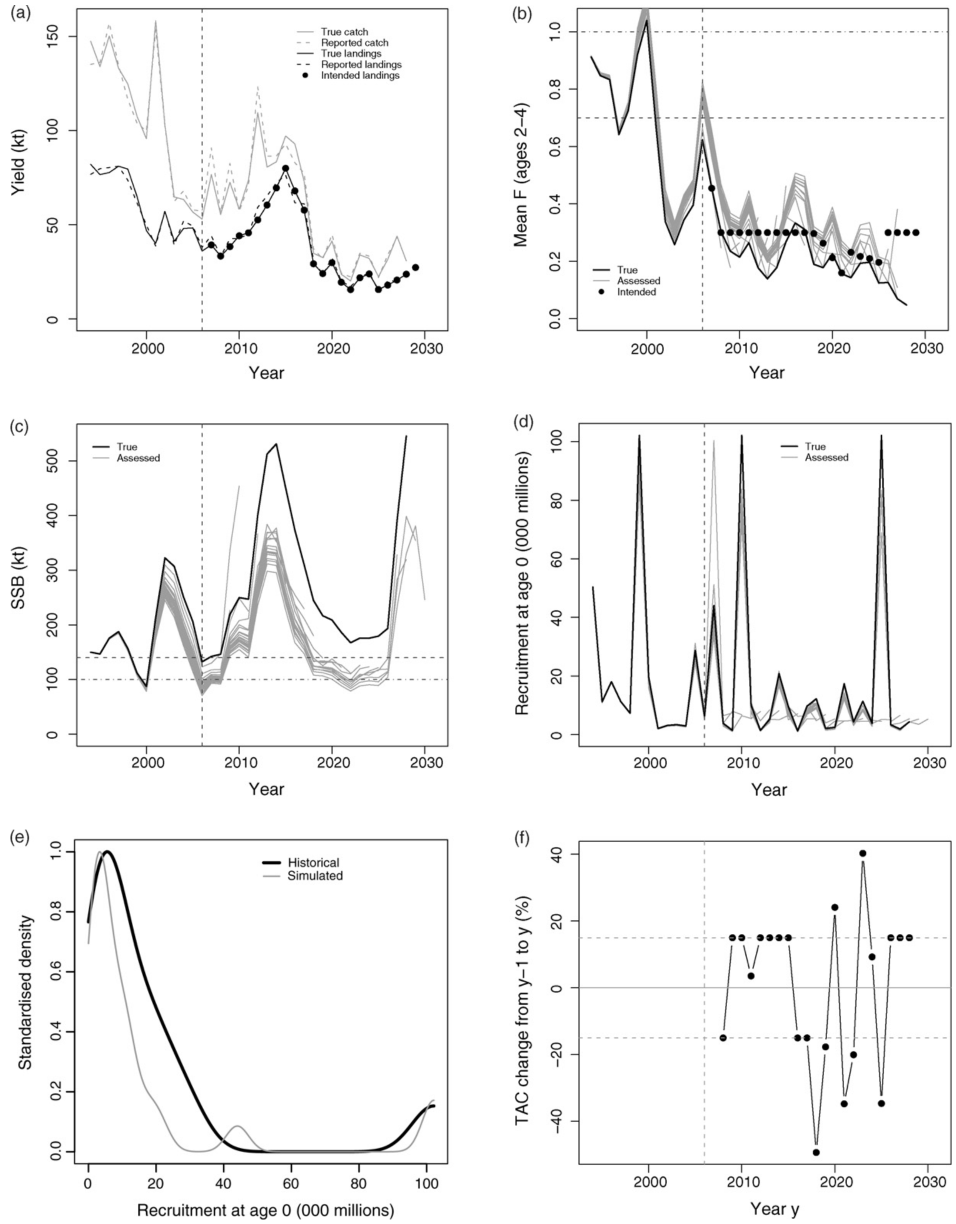

Fig. 6. Summary plots of a single simulation iteration, with $F_{target} = 0.3$. In each plot the vertical dashed line delineates the assessment year γ. Each grey line shows the assessment result for one year in the future simulation. (a) Yield. (b) Fishing mortality, with dashed horizontal lines indicating F_{lim} (upper) and F_{pa} (lower). (c) True (black) and assessed (grey) spawning-stock biomass B, with dashed horizontal lines indicating B_{pa} (upper) and B_{lim} (lower). (d) True (black) and assessed (grey) recruitment to the fished stock. (e) Comparison of frequency distribution of historical and simulated recruitment. (f) The percentage interannual change in quota (TAC), with dashed horizontal lines showing the ±15% level.

steady state of around 45 kt. Median fishing mortality is, for much of the time series, much lower than the F_{target} that the management plan should provide; this is due to a combination of the ±15% TAC constraint and the simple discard model mentioned above. Median biomass remains stable for four years or so, before rising swiftly and rebounding to a steady state well above B_{pa}. Finally, the median recruitment is low, but the occasional large year-classes are also evident.

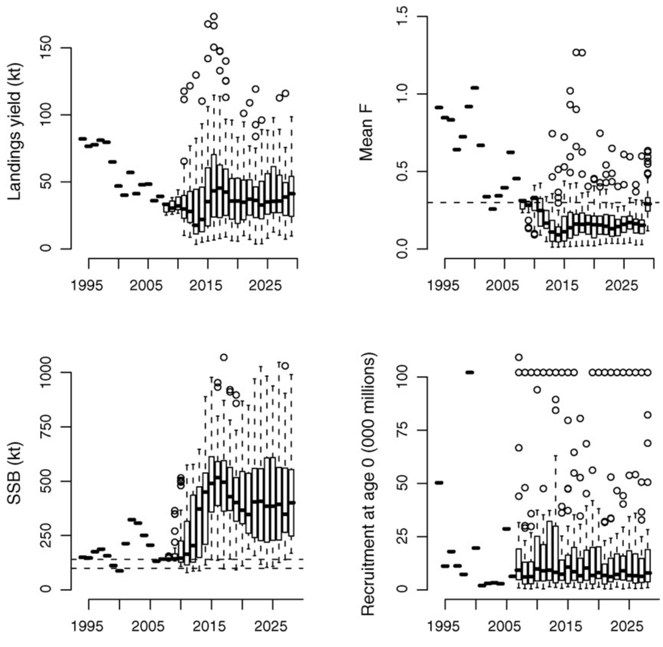

Fig. 7. Summary plots of 50 simulation iterations, with $F_{\text{target}} = 0.3$. The short horizontal lines indicate the medians, the boxes the quartiles (25th and 75th percentiles), and the whiskers the 5th and 95th percentiles. Outliers are shown by open circles. The dashed line on the top-right plot shows F_{target}, while those on the bottom-left plot show B_{pa} (upper) and B_{lim} (lower). Historical estimates (pre-2007) are shown as short horizontal lines only.

As well as medians, Fig. 7 also indicates the spread of possibilities, and on this basis we can examine the risk of occurrence of unwanted events. One such event would be biomass falling below B_{pa} or B_{lim}, which is what the management plan is attempting to avoid. We can estimate this risk by counting the number of years in a given iteration that $B < B_{\text{pa}}$ or $B < B_{\text{lim}}$. If we denote the spawning stock biomass in year y in iteration k of a simulation using F_{target} by $B_{y,k,F}$, allow B_{ref} to stand for B_{pa} or B_{lim} as appropriate, and use a selection function $\kappa_{y,k,F}$ such that

$$\kappa_{y,k,F} = \begin{cases} 1, & B_{y,k,F} < B_{\text{ref}} \\ 0, & B_{y,k,F} \geq B_{\text{ref}} \end{cases} \tag{1}$$

then the required risk is given by

$$\text{Risk}_{k,F} = \sum_{y} \kappa_{y,k,F}. \tag{2}$$

The distributions and central tendencies of $\text{Risk}_{k,F}$ are then used to indicate the degree of risk associated with each management measure (which in this case means each value of F_{target}).

The risk estimates for each F_{target} are summarised in Fig. 8, which considers the risk of both $B < B_{\text{pa}}$ and $B < B_{\text{lim}}$. The distributions of $\text{Risk}_{k,F}$ for both have had loess smoothers passed through them, to give an indication of the central tendency of risk. On the basis of these smoothers, the number of years for which $B < B_{\text{lim}}$ ranges from 0.26 years (which is 1.18% of the total) to 1.90 years (8.64%), while the values for $B < B_{\text{pa}}$ range from 1.73 years (7.86%) to 4.32 years (19.64%). That is, the risk of spawning biomass being below the limit reference point for the next 22 years, given the assumptions of the model, remain less than 10% for values of F_{target} as high as 0.5. The results for $F_{\text{target}} = 0.3$, the value stipulated in the management plan, are 0.46 years (2.10%) for $B < B_{\text{lim}}$ and 2.35 years (10.70%) for $B < B_{\text{pa}}$.

In any stock simulation of this kind, one of the key aspects to get right (if only approximately so) is the time-series of future recruitments. The assumption in this paper of two strong year classes over the next 20 years is a strong one. It is possible that the risk

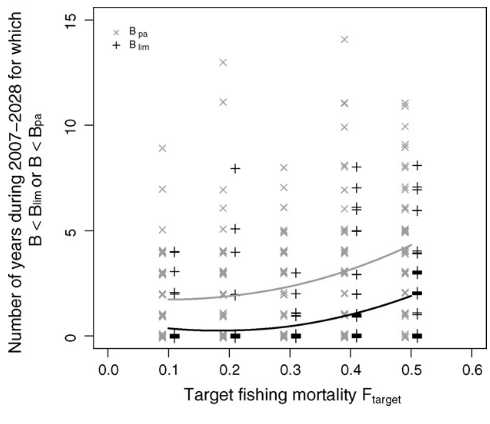

Fig. 8. Summary of risk of $B < B_{\text{pa}}$ (grey) and $B < B_{\text{lim}}$ (black) for different values of F_{target}. The correspondingly-coloured solid lines show the fits of loess smoothers to the full time-series of risk estimates. Small random perturbations have been applied to the vertical position of each cross to improve visualisation. Risk is defined as the number of years in each simulation for which spawning stock biomass $B < B_{\text{pa}}$ or $B < B_{\text{lim}}$ as appropriate.

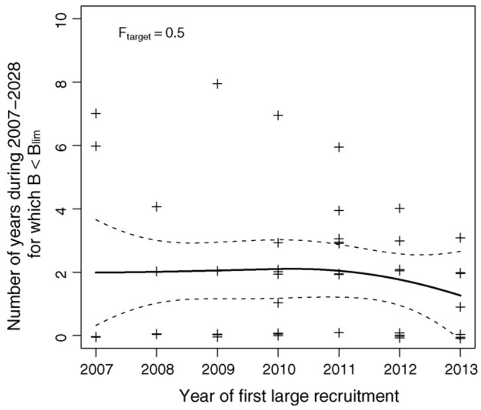

Fig. 9. The relationship between risk and the simulation year in which the first large recruitment event occurs. Risk is defined here as the number of years in each simulation for which spawning stock biomass $B < B_{\text{lim}}$. Each cross gives the result for one of the 50 simulations performed, in this case with $F_{\text{target}} = 0.5$, and small random perturbations have been applied to the vertical position of each cross to improve visualisation. The solid line shows a loess smoother passed through the data, while the dotted lines give ±2 standard errors of the smoother.

estimates described above are largely or entirely dependent on the year of occurrence of the first large year-class, the hypothesis being that the early appearance of this year-class would a necessary condition for low risk. This is tested in Fig. 9, which shows $\text{Risk}_{k,F}$ for $F_{\text{target}} = 0.5$ (and considering the risk of $B < B_{\text{lim}}$ in particular) plotted against the year of the first large recruitment in the corresponding simulation iteration. The plot does not support the hypothesis; if anything, the relationship between risk and the year of the first large recruitment is slightly negative. This result suggests that the simulations are not as closely dependent on the recruitment time-series as might be expected.

4. Discussion and conclusions

On the basis of the simulations presented in this paper, it would appear that the EU-Norway management plan for North Sea haddock is sustainable – that is, it provides a low risk of biomass being below the limit reference point, along with stability in quotas that will benefit the fishing industry and related economies. However, there are a number of caveats that need to be borne in mind. The analysis has assumed full implementation of the quota regulations, so that the landings are precisely as intended by the specified quota, neither above nor below. In reality many situations will prevent this happening: there may be misreporting by species or area, or quota uptake may be less than full (as has been the case in the North Sea during 2007). Fleet behaviour is assumed to be static, which is unlikely. The simulations also do not consider the impact of effort management or such technical measures as may be applied to the haddock fishery. Although these are not stipulated directly in the management plan, they do affect the fishery and will therefore have an effect on the sustainability of the plan when it is applied, as will multispecies considerations.

The biological assumptions in the analyses will also affect perceptions of the likely impact of the management plan. The growth of haddock is assumed to be constant into the future, although it is well known that haddock growth is affected by year class size (among other things; see ICES, 2007). Recruitment of haddock has been modelled as a time-series only, with no reference to parental spawning-stock size. The lack of a clear relationship between stock and recruitment would indicate that this is reasonable, but it means that good recruitment is possible in the simulations from extremely small adult stocks and this may not be realistic.

The simulations in this paper have been limited to 50 iterations each (due to time constraints). Generally, stochastic analyses of this kind would require 1000 or more iterations before reasonable conclusions could be drawn, and the small number used here leads to potential problems. For example, the recruitment distributions in Fig. 7 would all be similar if sufficient iterations had been run. That they are not may be introducing unwanted effects in the analysis. This problem is currently very hard to avoid: a run of 50 iterations takes around 15 h in the extant implementation, so that 1000 iterations would occupy over 12 days of computing time. There are a number of steps in the algorithm which slow the process down, including the live assessment, the iterative estimation of a TAC to produce a required fishing mortality rate, and the sliding-*F* rule. Work is ongoing to address this issue. However, the difficulty may not be as significant as it at first appears. The real difference between each iteration lies in the years in which the two large year-classes appear. While there are 56 possible permutations, there are only four combinations which are likely to have any real impact: the large year-classes can appear in the first or second half of 2006–2013, and first or second half of 2016–2023. That is, the large year-classes are either close together, moderately separated and early, moderately separated and late, or far apart. It may be that 50 iterations is sufficient to cover this reduced range of outcomes, particularly following the results in Fig. 9 which suggest that the recruitment time-series may not be all that critical.

The analyses suggest that one of the strongest influences on the simulated management is the assumption in the discard model that proportions discarded-at-age are invariant with time. This assumption is very clearly not true, and leads to consistent underestimation of biomass in the simulated assessment when large year-classes appear. The discrepancy between true and assessed *B* and *F* in these management simulations can be reduced by using a higher F_{target}, as this keeps biomass below the level at which discarding behaviour would be expected to change. It can also be ameliorated by allowing TACs to change without constraint. However, neither of these possibilities is allowed by the management plan, and the problem will therefore remain until an improved model of discarding is developed.

Indeed, all of the problems mentioned above are very difficult to address using currently-available knowledge. Given this, the best we can conclude is that the management plan appears to be sustainable in the context of a number of fairly crude (and possibly untestable) assumptions. However, this in itself is a valuable conclusion for fisheries managers, and is certainly more useful than no evaluation at all. The development of the evaluation has also been instructive, both in terms of generating a template in which other management plans can be evaluated, and in terms of highlighting issues with management for this particular fishery (such as discard modelling) which strongly affect the evaluation in unexpected ways – and which therefore need to be considered in more detail. Other important avenues for future work include evaluations of the effect of a "banking and borrowing" provision, whereby quota can be banked in one year to be used in the next, or borrowed from next year to be used in this (interannual flexibility); methods by which multispecies aspects can be incorporated; analyses to evaluate the sensitivity of outcomes to model assumptions (including the starting conditions and recruitment simulation); code optimisation to allow for more iterations; and ways in which the impact of other fisheries (such as industrial bycatch) can be incorporated in the evaluation.

Properly specified management-strategy evaluations, carried out using simulation methods, are the best (and perhaps only) way in which the structure, details and inherent risk of management plans can be tested, short of impractical real-world experimentation (Cooke, 1999; De Oliveira and Butterworth, 2004; Kell et al., 2006a; Aranda and Motos, 2006; Kell et al., 2006b). While it is possible to determine values for reference or trigger points without an MSE, using considerations of biology, fisheries, economics, and so on, it is difficult to test the effect of using any particular reference point in management (and thereby justify that point) without an MSE. Without an MSE, it is also impossible to claim with any certainty that a given plan will do what is intended. Although many difficulties remain, the development of MSE methods has been an important step forward in fisheries management science.

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Appendix A. The EU-Norway management plan for North Sea haddock

The text of the revised EU-Norway management plan for North Sea haddock, which came into effect on 1st January 2007, is as follows. TAC here stands for Total Allowable Catch; in fact this refers only to landings, not catch.

(1) Every effort shall be made to maintain a minimum level of Spawning Stock Biomass greater than 100 kt (B_{lim}).
(2) For 2007 and subsequent years the Parties agreed to restrict their fishing on the basis of a TAC consistent with a fishing mortality rate of no more than 0.3 for appropriate age-groups, when the SSB in the end of the year in which the TAC is applied is estimated above 140 kt (B_{pa}).
(3) Where the rule in paragraph 2 would lead to a TAC which deviates by more than 15% from the TAC of the preceding year the Parties shall establish a TAC that is no more than 15% greater or 15% less than the TAC of the preceding year.
(4) Where the SSB referred to in paragraph 2 is estimated to be below B_{pa} but above B_{lim} the TAC shall not exceed a level which will result in a fishing mortality rate equal to $0.3 - 0.2 \times (B_{\text{pa}} - \text{SSB})/(B_{\text{pa}} - B_{\text{lim}})$. This consideration overrides paragraph 3.
(5) Where the SSB referred to in paragraph 2 is estimated to be below B_{lim} the TAC shall be set at a level corresponding to a total fishing mortality rate of no more than 0.1. This consideration overrides paragraph 3.
(6) In order to reduce discarding and to increase the spawning stock biomass and the yield of haddock, the Parties agreed that the exploitation pattern shall, while recalling that other demersal species are harvested in these fisheries, be improved in the light of new scientific advice from *inter alia* ICES.
(7) In the event that ICES advises that changes are required to the precautionary reference points B_{pa} (140 kt) or B_{lim} (100 kt) the parties shall meet to review paragraphs 1–5.
(8) No later than 31 December 2009, the parties shall review the arrangements in paragraphs 1–7 in order to ensure that they are consistent with the objective of the plan. This review shall be conducted after obtaining *inter alia* advice from ICES concerning the performance of the plan in relation to its objective.

Appendix B. The evaluation algorithm

For those who wish to replicate the analysis or understand more fully the simulations presented in this paper, I have given a detailed description of the algorithm below. The method is also summarised schematically in Fig. 3. Throughout, a denotes age and y year, so $F_{a,y}$ gives (for example) the value of fishing mortality in age a and year y. The matrix of fishing mortalities for all ages and years is denoted by $\mathbf{F} = [F_{a,y}]$. $\hat{F}_{a,y}$ is the estimated fishing mortality, while $\tilde{F}_{a,y}$ gives the fishing mortality *intended* by management. For fishing mortality in particular, a missing a indicates the mean over ages 2–4: that is, $F_y = (1/3)(F_{2,y} + F_{3,y} + F_{4,y})$. For parsimony, we define the target fishing mortality as

$$F_{\text{target}} = \frac{1}{3}\sum_{a=2}^{4} \tilde{F}_{a,y}.$$

The initial assessment year (the first year in the simulation) is denoted by γ.

(1) Assessment working group data for North Sea haddock are read in. These are taken from the most recent assessment meeting (ICES, 2007), and consist of time series by age on landings and discards (both numbers and mean weights), stock weights, natural mortalites, maturities, and research-vessel survey indices.
(2) Assessment data for total catch numbers $C_{a,y}$ and yield Y_y are derived from data on landings and discards.
(3) Model and management parameters are set. These include biological reference points, age ranges over which to calculate mean F, the plus-group age a_{pg}, and assessment model settings.
(4) An initial XSA assessment (Shepherd, 1992; Darby and Flatman, 1994) is run, using data up to and including year $\gamma - 1$ (which is 2006 in the case study). The FLR implementation (FLXSA) is used here. This generates estimates of abundance $\hat{N}_{a,y}$, recruitment $\hat{R}_y = \hat{N}_{0,y}$ (age 0 is the first age in the North Sea haddock dataset), and fishing mortality $\hat{F}_{a,y}$, and enables subsequent estimation of the following:
    (a) Catchability $q_{i,a}$ for each survey. This is assumed to be related to estimated abundance via a power relationship, and is estimated for each survey i and age a by minimising the sum-of-squares

$$\text{SSQ}_q = \sum_y \left(I_{i,a,y} - \hat{q}_{i,a}\hat{N}_{a,y}^{\hat{p}_{i,a}}\right)^2, \tag{B.1}$$

    where $p_{i,a}$ is the power term in the catchability relationship for each age a and survey i.
    (b) Parameters of simulated recruitment. These are the mean and variance of the low-to-moderate recruitments observed during 1995–1998 and 2000–2006, and the estimate of the high 1999 year-class recruitment.
    (c) Selection ζ_a. This is a measure of how fishing mortality F varies with age a, and is given for each age by the mean of the last three historical F estimates. If γ is the first assessment year ($\gamma = 2007$ in the case study), then:

$$\zeta_a = \frac{1}{3}(\hat{F}_{a,\gamma-3} + \hat{F}_{a,\gamma-2} + \hat{F}_{a,\gamma-1}). \tag{B.2}$$

    This is then rescaled so that $\sum_a \zeta_a = 1$. In simulations modelling effort-based management, selection ζ_a must be assumed to be known throughout the simulation period: if this were not the case, there would be no unique solution to the estimation of F that results in the required catch. In this case study ζ_a is assumed to be fixed throughout the simulation period, although more complicated models of time-varying ζ_a would be possible.

(d) The proportions of the total catch numbers in each of the catch components (landings and discards) is fixed through the simulation period. They are based on three-year historical means, as follows:

$$\text{Landings}: \ \rho_a^{\mathrm{l}} = \frac{1}{3}\sum_{y=2004}^{2006}\frac{C_{a,y}^{\mathrm{l}}}{C_{a,y}^{\mathrm{l}}+C_{a,y}^{\mathrm{d}}} \tag{B.3}$$

$$\text{Discards}: \ \rho_a^{\mathrm{d}} = 1-\rho_a^{\mathrm{l}} \tag{B.4}$$

(5) Data objects are stipulated, and run settings defined. The settings used in the North Sea haddock case study are as follows:

Survey CV : $\sigma_i = 0.2$
Catch CV : $\sigma_{\mathrm{c}} = 0.1$
Management type : TAC – based landings regulation
HCR type : Management plan with sliding – F rule
Limit in TAC change : $\Delta\mathrm{TAC} = 0.15(15\%)$
Target F : $F_{\mathrm{target}} = 0.1, 0.2, 0.3, 0.4, 0.5$
Bycatch F : $F_{\mathrm{bycatch}} = 0.1$
Limit in F change : $\Delta F = 0.25(25\%)$
Biomass reference points : $B_{\mathrm{lim}} = 100\,\mathrm{kt}$,$B_{\mathrm{pa}} = 140\,\mathrm{kt}$

(6) The analysis itself consists of three concentric loops: the F_{target} loop, which considers different values of F_{target}; the k or iteration loop, which loops over different randomly-generated recruitments, and the inner y or year loop. The y-loop proceeds as follows:

(a) If $y = 1$, $F_{a,y}$ (the intermediate year fishing mortality) is set to the mean of the last three historical years. If $y > 1$, this step is not required as the intermediate-year F is determined by previous applications of the specified HCR.

(b) Recruitment in year y is given by

$$R_y = \begin{cases} R_y^{\mathrm{high}} & y = y_1, y_2 \\ R_y^{\mathrm{low}} & \text{otherwise} \end{cases} \tag{B.5}$$

where

$$\ln R_y^{\mathrm{low}} \sim N(\bar{R}^{\mathrm{low}}, \mathrm{CV}R_y), \tag{B.6}$$

$$\bar{R}^{\mathrm{low}} = \exp\left(\frac{1}{10}\sum_{y=95\ldots98,00\ldots05}\ln R_y\right) \tag{B.7}$$

and

$$\mathrm{CV}(R_y) = \mathrm{sd}(\ln R_{95},\ldots,\ln R_{98},\ln R_{00},\ldots,\ln R_{05}). \tag{B.8}$$

In addition

$$y_1 \sim U(2006, 2013) \tag{B.9}$$

$$y_2 \sim U(2016, 2023) \tag{B.10}$$

and

$$R_{y_1,y_2}^{\mathrm{high}} \sim N(R_{99}, 0.1R_{99}). \tag{B.11}$$

(c) Biological parameters are assumed to be constant throughout the simulation, so that for any a and y:

$$\text{Catch weights}: W_{a,y}^{\mathrm{c}} = W_{a,y-1}^{\mathrm{c}} \tag{B.12}$$

$$\text{Landings weights}: W_{a,y}^{\mathrm{l}} = W_{a,y-1}^{\mathrm{l}} \tag{B.13}$$

$$\text{Discard weights}: W_{a,y}^{\mathrm{d}} = W_{a,y-1}^{\mathrm{d}} \tag{B.14}$$

$$\text{Stock weights}: W_{a,y}^{\mathrm{s}} = W_{a,y-1}^{\mathrm{s}} \tag{B.15}$$

$$\text{Natural mortality}: M_{a,y} = M_{a,y-1} \tag{B.16}$$

$$\text{Maturity}: \mathrm{Mat}_{a,y} = \mathrm{Mat}_{a,y-1} \tag{B.17}$$

$$\text{Prop. F before spawning}: \mathrm{PF}_{a,y} = \mathrm{PF}_{a,y-1} \tag{B.18}$$

$$\text{Prop. M before spawning}: \mathrm{PM}_{a,y} = \mathrm{PM}_{a,y-1} \tag{B.19}$$

(d) Abundance in year y for all $a < a_{\mathrm{pg}}$ is given by

$$N_{a,y} = N_{a-1,y-1}\exp(-F_{a-1,y-1} - M_{a-1,y-1}), \tag{B.20}$$

and for $a = a_{\mathrm{pg}}$:

$$N_{a,y} = N_{a-1,y-1}\exp(-F_{a-1,y-1} - M_{a-1,y-1}) + N_{a,y-1}\exp(-F_{a,y-1} - M_{a,y-1}). \tag{B.21}$$

(e) Catch, landings and discard numbers C (as well as associated yields Y) in year y are now calculated, using

$$C_{a,y}^{\mathrm{c}} = \frac{\tilde{F}_{a,y}N_{a,y}(1-\exp(-\tilde{F}_{a,y}-M_{a,y}))}{\tilde{F}_{a,y}+M_{a,y}} \tag{B.22}$$

$$C_{a,y}^{\mathrm{l}} = \rho_a^{\mathrm{l}}C_{a,y}^{\mathrm{c}} \tag{B.23}$$

$$C_{a,y}^{\mathrm{d}} = \rho_a^{\mathrm{d}}C_{a,y}^{\mathrm{c}} \tag{B.24}$$

$$Y_y^{\mathrm{c}} = \sum_a C_{a,y}^{\mathrm{c}}W_{a,y}^{\mathrm{c}} \tag{B.25}$$

$$Y_y^{\mathrm{l}} = \sum_a C_{a,y}^{\mathrm{l}}W_{a,y}^{\mathrm{l}} \tag{B.26}$$

$$Y_y^{\mathrm{d}} = \sum_a C_{a,y}^{\mathrm{d}}W_{a,y}^{\mathrm{d}} \tag{B.27}$$

Note that $\tilde{F}_{a,y}$ here is the *intended* fishing mortality produced by a previous management decision. Under catch-based management, Eq. (B.22) cannot be used directly because it is intended landings yield $\tilde{Y}_y^{\mathrm{l}}$ that is determined by a previous management decision, not fishing mortality $\tilde{F}_{a,y}$. In this case, a multiplier λ_y must be determined such that the application of $F_{a,y} = \lambda_y\zeta_a$ results in $N_{a,y} > 0\ \forall\ a$ and $Y_y^{\mathrm{l}} \leq \tilde{Y}_y^{\mathrm{l}}$. Recall that ζ_a is the selection at age a from Eq. (B.2). Here we are modelling a fishery which will take the predetermined TAC if possible, but not if doing so would result in negative abundance at any age. λ_y is estimated by minimising the sum-of-squares between intended yield $\tilde{Y}_y^{\mathrm{l}}$ and actual yield Y_y^{l}, constrained so that $N_{a,y} > 0\ \forall\ a$. Once this is done, fishing mortality is given by $F_{a,y} = \lambda_y\zeta_a$ and catch by Eq. (B.22).

(f) Survey indices are now generated for year y: note that these are not actually used in the assessment until the following year, but it is convenient to generate them at this point in the cycle. Given catchability $q_{i,a}$, abundance $N_{a,y}$ and a random term $\varepsilon_{a,y}^{i} \sim \mathrm{N}(0,\sigma_i^2)$, survey indices are given by

$$I_{i,a,y} = q_{i,a}N_{a,y}^{p_{i,a}}\exp(\varepsilon_{a,y}^{i}). \tag{B.28}$$

(g) Catch, landings and discards data for assessments are produced by applying random noise to true values. Given an assumed measurement error variance on catch data of σ_{c}, assessment catch data is given by

$$\hat{\mathbf{C}}^{\mathrm{c}} = [\hat{C}_{a,y}^{\mathrm{c}}] = [C_{a,y}^{\mathrm{c}}\exp(\varepsilon_{a,y}^{\mathrm{c}})], \tag{B.29}$$

where $\varepsilon^{c}_{a,y} \sim N(0, \sigma^2_c)$. Assessment landings and discards data are generated in an analogous manner to true landings and discards data:

$$\hat{\mathbf{C}}^{l} = [\hat{C}^{l}_{a,y}] = [\rho^{l}_{a}\hat{C}^{c}_{a,y}] \tag{B.30}$$

$$\hat{\mathbf{C}}^{d} = [\hat{C}^{d}_{a,y}] = [\rho^{d}_{a}\hat{C}^{c}_{a,y}] \tag{B.31}$$

Measured yields $\hat{\mathbf{Y}}^{c}$, $\hat{\mathbf{Y}}^{l}$ and $\hat{\mathbf{Y}}^{d}$ are calculated in a similar way to that given in Eqs. (B.25)–(B.27).

(h) An assessment is carried out, using data (up to and including year $y-1$) for $\hat{\mathbf{C}}^{c}$, $\hat{\mathbf{Y}}^{c}$, $\mathbf{W}^{c}$, $\mathbf{W}^{s}$, **M**, **Mat**, **PF**, **PM**, and **I**(see Eqs. (B.12)–(B.19)). The FLXSA function of FLR is used for this purpose, and returns assessment estimates of abundance $\hat{\mathbf{N}}$ and fishing mortality $\hat{\mathbf{F}}$. In the first year loop only ($y = 2007$) these estimates are treated as the true values, so that:

$$N_{a,j} = \hat{N}_{a,j} \tag{B.32}$$

$$F_{a,j} = \hat{F}_{a,j} \tag{B.33}$$

for $j \leq y-1$.

(i) At this point we apply the sliding-*F* management rule. An *F*-multiplier F^{m} is estimated that results in $F_{y+1} = F_{\text{target}}$ when applied to $\hat{F}_{y-1}$. A short-term (three-year) forecast is carried out on the basis of this value of fishing mortality, using year $y-1$ as the starting point, and the resultant spawning-stock biomass $\hat{B}_{y+2}$ in the year following the quota year is generated. If $\hat{B}_{y+2} < B_{\text{pa}}$, the sliding-*F* rule is applied to generate a new F_{target} and the forecast procedure is repeated to produce a new $\hat{B}_{y+2}$. This may imply a different F_{target}, in which case the procedure is repeated until the difference between subsequent values of F_{target} is less than a pre-specified iteration tolerance. This iteration nearly always converges: if $\hat{B}_{y+2}$ flips between a value above B_{pa} and a value below B_{lim}, then the average of F_{target} and F_{bycatch} is used.

If the final $\hat{B}_{y+2} > B_{\text{pa}}$, the TAC constraint is applied ($\Delta\text{TAC} = 15\%$, in this case). The implied intended landings yield $\tilde{Y}^{l}_{y+1}$ is compared with $\tilde{Y}^{l}_{y} \pm \Delta\text{TAC}$. If $\tilde{Y}^{l}_{y+1}$ is within this range, then the intended yield is set to that which is implied by $\tilde{F}_{y+1} = \hat{F}_{y-1} \times F^{m}$. On the other hand, if the implied yield $\tilde{Y}^{l}_{y+1}$ from the original forecast is *not* within the bounds specified by ΔTAC, then $\tilde{Y}^{l}_{y+1}$ is set to $\tilde{Y}^{l}_{y} \pm \Delta\text{TAC}$.

A series of low recruitments can lead to an exponential (and irreversible) increase in *F* as our virtual managers try to ensure that the full TAC is taken. To prevent this, a limit ΔF is stipulated on interannual change in *F*. If $F^{m} > 1.0 + \Delta F$ then F^{m} is set to $1.0 + \Delta F$: similarly, if $F^{m} < 1.0 - \Delta F$ then F^{m} is set to $1.0 - \Delta F$. It is also useful to record intended yield, which in this case is the yield implied by the modified F^{m}.

Although the process is quite complicated, the output from the evaluation is simple: the intended landings yield $\tilde{Y}^{l}_{y+1}$.

(j) With management decisions now determined, the *y*-loop carries on to the start of the next year. The quota year from the previous *y*-iteration now becomes the intermediate year, and effect of fishing on the stock is now largely determined by the intended yields.

(k) Once the *y*-loop is completed, the simulation begins again with the next *k*-loop and a different time-series of recruitments, and subsequently the next F_{target}-loop.

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Evaluating the effect of real-time closures on cod targeting

Coby L. Needle* and Rui Catarino

Marine Scotland, Marine Laboratory, PO Box 101, 375 Victoria Road, Aberdeen AB11 9DB, Scotland, UK

**Corresponding Author: tel: +44 1224 295456; fax: +44 1224 295511; e-mail: needlec@marlab.ac.uk.*

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Under its Conservation Credits scheme to reduce cod mortality, the Scottish Government has implemented a system of real-time closures (RTCs) since 2008. These are relatively small, temporarily closed areas (50–225 square nautical miles per RTC, closed for 21 d) that are triggered by high cod catches. An important step in evaluating their effectiveness is to determine the response of vessels to RTCs, because the conservation benefit would be reduced if vessels moved to areas of greater cod abundance following closures. Abundance indices from research-vessel surveys and commercial-vessel observer trips are combined to create a time- and space-dependent relative cod-importance index (RCII). Vessel monitoring system data from Scottish vessels fishing during 2008/2009 are used to construct RCII profiles for each vessel, which are then used to determine whether the areas to which vessels move have a higher or a lower RCII, and how far away they move when an RTC is activated. We show that the RCII of the areas moved to tends to be lower than that of the RTC and that vessels travel farther when moving away from a closure than when moving back after reopening. Although not conclusive, this result indicates that RTCs may impact beneficially on cod mortality.

Keywords: closed areas, cod, fleet dynamics, relative importance index, VMS data.

Introduction

Scientific advice for fishery management has always been based on limited data. Catch data often do not include discards, and survey indices are derived from brief snapshots of stock abundance and distribution. Such limitations often hamper the ability of scientists to help managers to take appropriate decisions. Historically, one of the key missing pieces of information has been the location of fishing effort. Without good data on where vessels have been fishing, it has been very difficult to devise and implement appropriate management measures that take account of the spatial distributions of fish or fleets.

Although not without problems, the recent availability of vessel monitoring system (VMS) data to scientists has permitted a wide range of analyses that would not previously have been possible (see, e.g. Lee *et al.*, 2010; Vermard *et al.*, 2010; Gerritsen and Lordan, 2011). The example considered in this paper is the response of Scottish skippers to the implementation of real-time closures (RTCs), which are part of the Scottish Government's response to European Union (EU) calls for reductions in cod (*Gadus morhua*) mortality. Using VMS data and a derived spatio-temporal distribution indicating the relative importance of cod, we analyse the movements of those vessels thought to be most directly affected by RTCs. Specifically, we determine whether vessels moving away from closed areas (or back towards reopened areas) increase or decrease their likely impact on cod mortality, as measured by the RCII (relative cod-importance index) in the areas in which they are fishing. Although the analysis is useful in itself for evaluating the impact of management measures on cod mortality, it is also valuable as an example of how to use fishery-dependent information to provide management advice that would not otherwise be obtainable.

Data

Since 2003, monitoring systems of the VMS type have been installed on Scottish fishing vessels longer than 15 m, ostensibly with two main purposes: to assist in search-and-rescue operations and to enable compliance officials to know where a vessel was at a given time (and whether it was transgressing in closed areas, for example). The potential value of VMS data to scientists studying fleet behaviour and producing stock assessments was clear immediately, but permission for Scottish fishery scientists to access VMS data was granted by the Scottish fishing industry only in 2007 (Gatt and Reid, 2007). Since then, scientists from government laboratories (Marine Scotland) have been allowed to use such data for research purposes. However, such access is limited to studies concerning the Common Fisheries Policy (CFP) of the EU and associated issues.

VMS data consist of vessel speeds, headings, and locations, with one reading (known as a "ping") being transmitted to a central repository via a satellite link every 2 h. The data are actually generated at a much higher frequency (as much as once every 10 s), but the limitation to one ping every 2 h reduces the cost of satellite transmissions. Even at this frequency, there are often periods of missing data in the VMS database; these transpire for various reasons, principally faulty equipment. The database used for this study contains VMS records for all Scottish non-pelagic vessels (>15 m) fishing during the period specified.

Restrictions on the use of VMS data

Dissemination and transmission of Scottish VMS data to the public are not permitted. The Freedom of Information (Scotland) Act does not apply, because VMS data are considered to be sensitive personal information and are protected under EU law. However, it is important to note what are and what are not considered to be VMS data. The term is intended to cover data that identify individual vessels and reveal their speed, position, and heading while at sea. Our interpretation of recent legal advice indicates that suitably anonymized plots of vessel positions and speeds are not VMS data and can be included in publicly available documents.

In this context, it is important to be able to generate plots that summarize a vessel's position and speed in a way that does not reveal its identity or exact fishing location, because this is commercially sensitive information that would be illegal to present. Standard plots of VMS positions are not appropriate for this purpose. In this paper, a system of data binning is used to present VMS information at a suitable level of aggregation. However, the analyses are carried out using exact-position 2-h VMS ping data, so the accuracy of vessel positions is not compromised.

VMS data do not indicate directly what a vessel is doing at a particular location. Borchers and Reid (2008) used probabilistic activity models to conclude, for demersal trawlers, that only those moving at speeds of 0.5–5 knots were likely to be fishing. Recent analyses comparing VMS and closed-circuit television data from Scottish vessels support this speed range (unpublished results), and it is used by the Scottish Government when determining areas to be closed. VMS fishing pings in the analysis here are therefore specified using the same speed criterion.

RTCs during 2008–2010

As part of its Conservation Credits initiative which began in 2008, the Scottish Government instigated a series of RTCs intended to divert demersal fishing effort away from areas of abundant cod, and hence to reduce cod mortality. The RTCs were stipulated as areas of ∼50 square nautical miles and were initially defined as 7 × 7 nautical mile squares,, although this limitation has subsequently been relaxed and RTCs may now be of different shapes. Since June 2010, the maximum possible area of each RTC has been increased to 225 square nautical miles. Each RTC is in place for 21 d, following which period they are reopened automatically. Further, the rules limit the number of RTCs that can be enacted simultaneously in proximity to prevent certain local fishing communities being unfairly disadvantaged. The closure of an area is triggered by an upper limit on the observed cod density, defined as 40 cod (of any size) per hour's fishing. Notification is via skipper's logbooks, monitored landings, or by on-board observation, and a single high-density haul is sufficient to instigate a closure. There may only be a maximum of 11 closures defined by logbook or landings data in operation at any one time, along with an additional three closures defined by positive

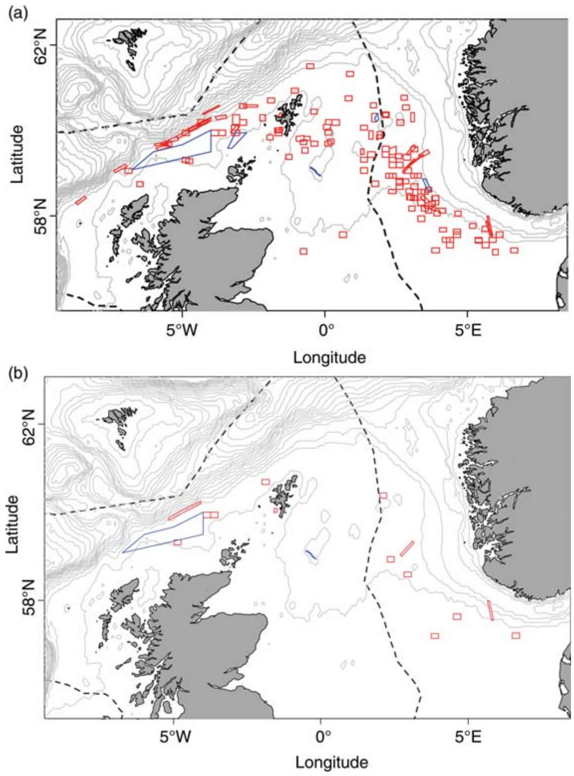

Figure 1. Area closures in (a) the whole of 2009, and (b) on 1 July 2009, showing both RTCs (red), and permanent or other seasonal closures (blue; see Holmes *et al.*, 2011). The dotted line shows the extent of the UK EEZ, and grey lines show bathymetry at 100-m intervals.

on-board samples. Since 2009, observance of RTCs by Scottish demersal fishing vessels has been mandatory. There is no legal impediment to vessels from other countries fishing in RTCs, although they have been encouraged by the Scottish Government and the EU not to do so, and anecdotal evidence from compliance officers and the Scottish fishing industry suggests that RTCs have generally been respected by non-Scottish vessels.

Full details on how RTCs are defined within the Conservation Credits scheme are given in Holmes *et al.* (2009): see also European Parliament (2010). In all, 15 such closures were implemented in 2008, but an expansion of the scheme led to 144 closures in 2009 (Figure 1a) and 165 in 2010. Although the area covered by the closures in 2009 looks substantial, it is important to note that only a few of the RTCs were in force on any given day: Figure 1b shows the extant closures on 1 July 2009.

Cod abundance data

To generate a spatio-temporal distribution of relative cod importance, and thereby to determine whether vessels moved towards or away from cod as a result of the area closures, reliable data on observed cod densities were required. Reported landings have limited utility for this purpose, because they do not include discards, which may be a sizeable component of the catch, and they are not very informative about where the fish were caught. The reported landings for a fishing trip might be assigned equally to all the VMS fishing-ping locations for that trip (see above), but this is imprecise and could be misleading. Appropriate models of fish distribution incorporating landings records are under development, but for this exercise, we considered that landings data could not be used for the analysis. The data used, therefore, come from a combination of research-vessel surveys and discard observations. For 2008 and 2009, they were:

(i) the North Sea International Bottom Trawl Survey (IBTS-NS, Q1 and Q3), carried out by several countries during the periods January/February and July–September and collated by ICES;

(ii) the Beam Trawl Survey (BTS Q3), conducted in the southern North Sea during August and September and also collated by ICES;

(iii) the Scottish Groundfish Survey in Division VIa (West of Scotland), carried out by Marine Scotland on RV "Scotia" during March (ScoGFS VIa Q1);

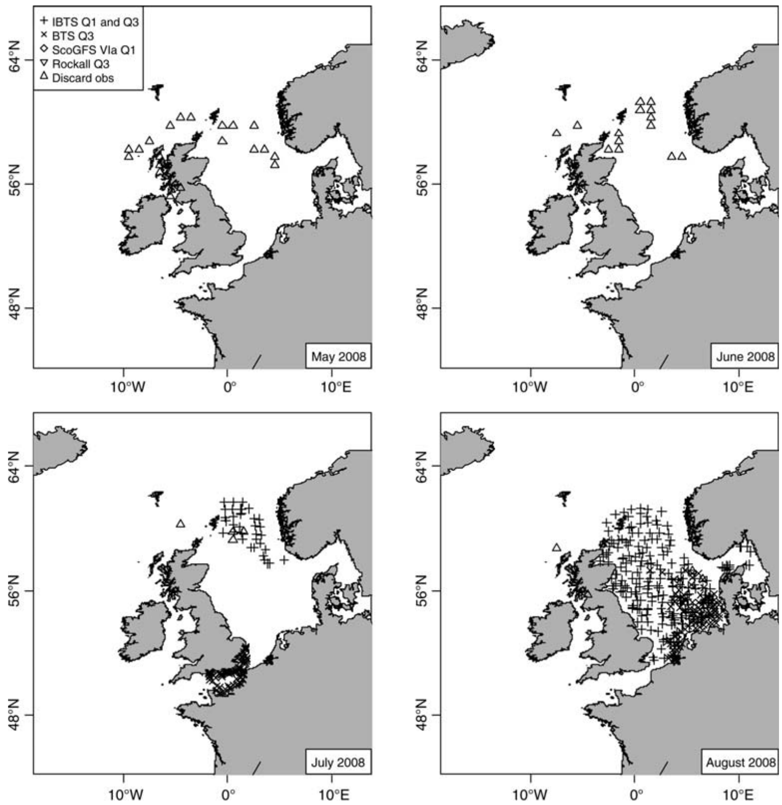

Figure 2. A subset of the cod-density observations used to generate the relative cod-importance index (RCII). Symbols indicate the locations of available observations for the period May–August 2008. Note that these dates do not include the ScoGFS VIa Q1 or Rockall Q3 surveys.

(iv) the Scottish Rockall survey (Rockall Q3), conducted by Marine Scotland on RV "Scotia" during September;

(v) Scottish discard observations, collated from ~75 observer trips each year.

Data were taken from the ICES DATRAS database (www.ices.dk) and the Scottish Fisheries Management Database (FMD) operated by Marine Scotland (www.scotland.gov.uk). The locations of cod observations for the period May–August 2008 are summarized in Figure 2.

Methods

The relative cod-importance index

To determine whether vessels moved to areas of greater or lesser cod density when displaced by the creation of an RTC, we developed an index of relative cod density (the relative cod-importance index, or RCII). In brief, it takes all available spatial distribution data on cod from research-vessel surveys and discard-observer trips for a given month, standardized to a consistent scale (the measurement units used by different surveys and observer programmes can vary widely), then fits a trend surface using generalized least squares. The procedure produces a contour plot of relative cod importance for each month. However, observations in a given month can be patchy; and for some months, there are no observations at all, so to improve the consistency of fitted distributions through time, there is an additional temporal-smoothing step in which the distribution at each point for a given month is modified by the equivalent values in preceding and succeeding months. Temporal smoothing is achieved using weighted local polynomial regression (loess) smoothers (Cleveland *et al.*, 1992), in which the weights are the Haversine distance (see below) from the point in question to the nearest points with actual observations in that month. Therefore, we generate a relative cod distribution using observed abundances, smoothed over both space and time to avoid problems inherent in the patchiness of the data. These analyses were carried out using R (version 2.8.1; R Development Core Team, 2008), with the "spatial" library (Venables and Ripley, 2002).

The RCII algorithm proceeds as listed below.

(i) The numbers of cod N caught per hour (by either a survey or an observed vessel) are extracted from the relevant datasets. Cod numbers from each data source are heavily skewed, with many zero observations and a few large ones. If used without any transformation, these data would lead to cod distribution maps consisting of a few hotspots, a pattern that does not reflect the industry perception of a widespread cod abundance on which fishing decisions are based. As we are attempting to model the consequences of such decisions, results based on non-transformed data would have little relevance. To improve the distributional properties of the data for the purposes of this analysis, therefore, a cube-root transformation $N^{1/3}$ is applied. However, the choice of transformation is *ad hoc*: zero-inflated models (Zuur *et al.*, 2009) would be examples of plausible alternatives.

(ii) The data are further rescaled so that the relative abundance over all observations for each source lies between 0 and 1 (considering all months together), avoiding problems with the original very different measurement units. This rescaled abundance is denoted by $\tilde{N}^{1/3}$.

(iii) Abundance data from all sources are collated into a single dataset, then split by month. The R function used to fit trend surfaces (see below) will fail if two or more

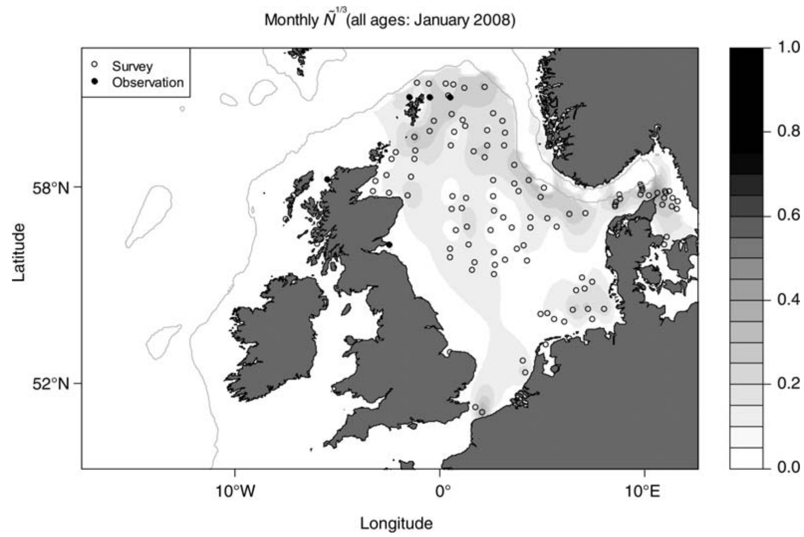

Figure 3. Fitted trend surface (without temporal smoothing) for rescaled cod abundance $\tilde{N}^{1/3}$ for January 2008. Grey lines indicate the 250-m depth contour, used to limit the study area. Darker areas indicate higher values of $\tilde{N}^{1/3}$. Open circles, data points from research-vessel surveys (in this case, IBTS NS Q1); closed circles, data from observer trips on commercial vessels.

observations have exactly the same position. To prevent these computational problems, small random perturbations are applied to the latitude–longitude position records of all observations.

(iv) The dataset for a given month now contains a list of rescaled abundances along with a unique latitude–longitude position marker for each. The R function "surf.gls" is used for each month to generate trend surfaces based on $\tilde{N}^{1/3}$ values. This approach assumes a heteroscedastic error structure in the underlying abundance distribution. As part of the fitting process, a mask is applied to ensure that land (depth < 0 m) and deep-water areas (depth > 250 m) are

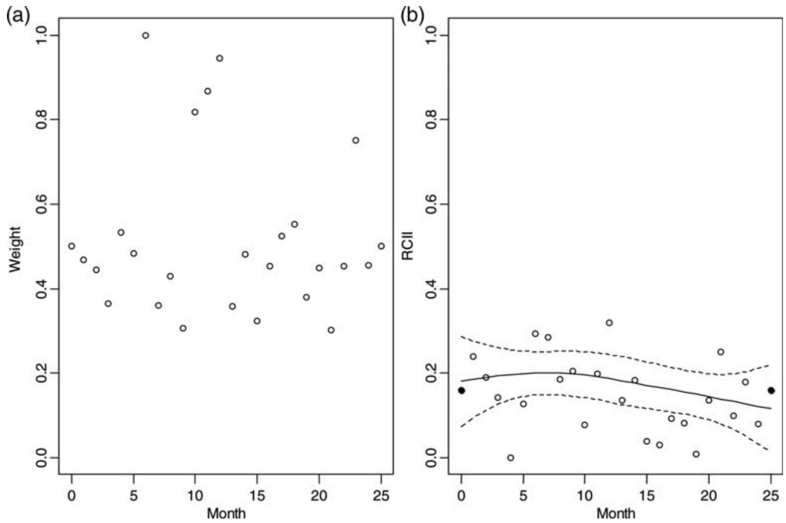

Figure 4. (a) Mean Haversine-distance weights for temporal loess index smoothing at a point off the east coast of Shetland, for 2008/2009. (b) Monthly relative cod-importance index (RCII) for 2008/2009, along with a weighted loess smoother (solid line) with 95% confidence limits (dotted lines). Solid points in months 0 and 25 indicate the means of the full time-series, which were included in the smoother estimation (with weights of 0.5) to prevent unrealistic boundary estimates.

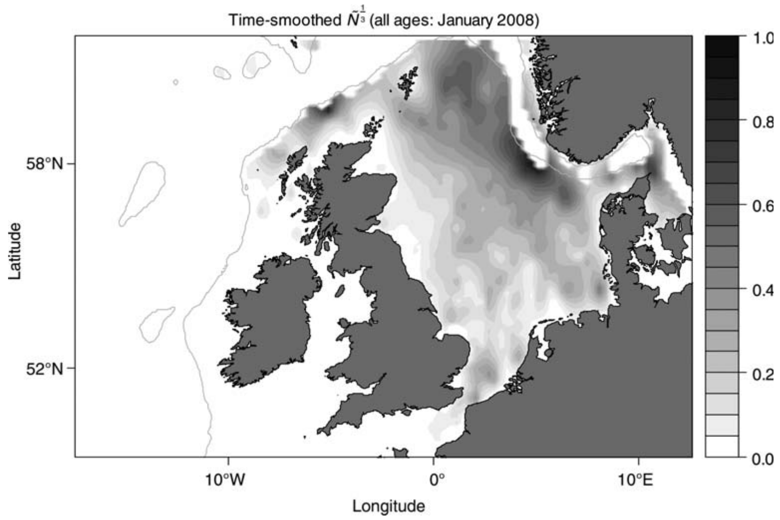

Figure 5. Fitted trend surface (with temporal smoothing) for rescaled cod abundance $\tilde{N}^{1/3}$ for January 2008. Grey lines indicate the 250-m depth contour used to limit the study area. Darker areas indicate higher values of $\tilde{N}^{1/3}$.

excluded from the fitted distribution, because cod are unlikely to be found in either. An example is given in Figure 3 (for January 2008).

(v) The next step is to apply temporal smoothing through a weighted loess regression time-series smoother. Weights are calculated using the mean inverse-Haversine distance of the point of interest (x_i, y_i) to the n available abundance observations for that month (see below).

(vi) The final step is to use all the smoothed index values for each month to generate a new smoothed-density map for that month.

For an angle θ, the Haversine function is given by

$$\mathrm{haversin}(\theta) = \sin^2\left(\frac{\theta}{2}\right), \quad (1)$$

and the Haversine formula (Gellert *et al.*, 1989) is then

$$\mathrm{haversin}\left(\frac{d}{R}\right) = \mathrm{haversin}(\varphi_2 - \varphi_1) + \cos(\varphi_1)\cos(\varphi_2)\,\mathrm{haversin}(\lambda_2 - \lambda_1), \quad (2)$$

where d is the spherical distance between points, R the radius of the sphere (in this case, the Earth), and (φ_1, λ_1) and (φ_2, λ_2) the latitude and the longitude of the first and the second points, respectively. The required distance can be calculated from Equation (2) using the inverse Haversine function. The weight $\omega_{i,m}$ for the ith point (x_i, y_i) in month m is then given by the mean d between the ith point and all other extant points in that month. This approach is used rather than Euclidean distances, because it accounts for the curvature of the Earth, but the Haversine formula assumes a perfectly spherical Earth (rather than the actual ellipsoid), and may be up to $\pm 0.5\%$ inaccurate.

The intention with this weighting scheme is to produce an estimate for a given point in a given month that depends strongly on nearby observations and is only weakly determined by distant observations. These weights are then used in a weighted loess smoother, which in addition to the monthly values includes the mean of the time-series as extra values in months 0 and 25, i.e. at the ends of the time-series. These extra values are given a weight of 0.5 each in the smoother and are intended to prevent potential extrapolation to negative values. The span of the loess smoother is set to 2.0, following exploratory analyses which indicated intuitively that this gave a reasonable balance between responsiveness and smoothness.

Generation of RCII difference metrics and distances moved

Given a spatio-temporal RCII, the next task is to determine those vessels which would be expected to be affected by RTCs. The full VMS dataset for 2008 and 2009 was partitioned by vessel. The VMS data for each vessel were then examined to determine if:

(A) the vessel had been fishing within an RTC area during the 15-d preceding closure;

(B) the vessel had been fishing in an RTC during the closure;

(C) the vessel had returned to the RTC area during the 15-d following reopening.

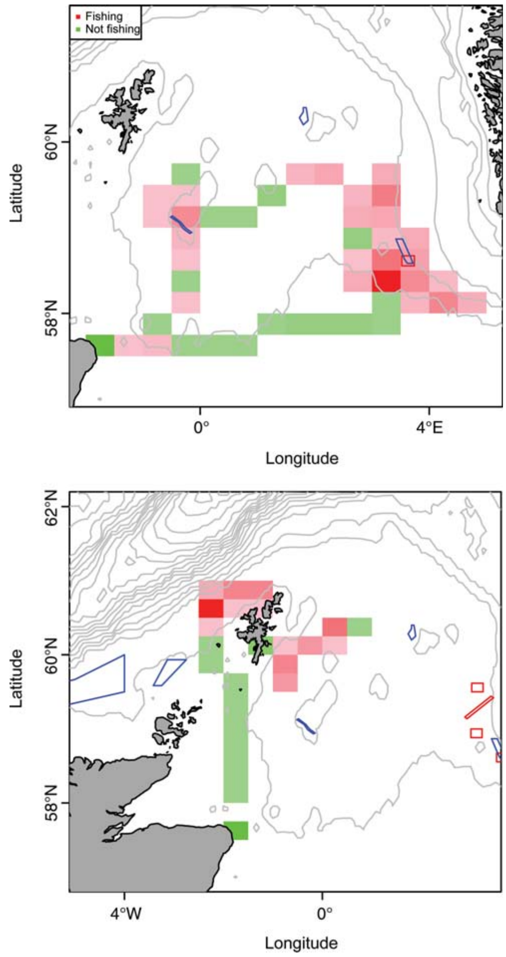

Figure 6. Aggregated VMS ping positions for vessel X during two consecutive trips in 2009. Aggregation bins are $0.5^\circ \times 0.25^\circ$ rectangles, shaded by ping abundance (darker colours indicate more pings). Note that only fishing pings are included in the scaling for those bins with both fishing and non-fishing pings. Red polygons indicate RTCs; blue polygons show permanent or other seasonal closures.

For each trip in which one of these criteria was met, the mean RCII for all VMS fishing ping locations during the trip was calculated. For cases A and B, the mean fishing-ping RCII for the following trip undertaken by the vessel was calculated; for case C, the mean fishing-ping RCII for the preceding trip was calculated. The mean RCII for the trip of interest was then compared with that from either the preceding or the following trip (the comparison trip), as appropriate. If the RCII for the trip of interest exceeded that for the comparison trip, it would indicate that the vessel had moved to an area of less importance for cod following the closure, although we cannot conclude that the closure was necessarily the reason for the move.

We also calculated the geographic midpoint of all the fishing pings for the trip of interest and for the comparison trip. The Haversine distance [Equations (1) and (2)] between the two VMS midpoints was used to approximate the distance moved between the areas fished in the two trips, and therefore how far the vessel had moved following the closure (cases A and B) or the reopening (case C).

Results

An example of the results of the weighting scheme for the RCII for a point east of Shetland is shown in Figure 4a. Figure 4b gives the smoothed time-series for the example point, showing some evidence (although not strong) for a decline in RCII for this example point through the study period. Figure 5 then gives the full result of the RCII algorithm for January 2008. The overall impression is of a cod distribution that is concentrated around the northern reaches of the North Sea, which is similar to what would have been expected from knowledge of survey data and the locations of good fishing grounds.

Figure 6 summarizes the VMS data for a particular vessel (vessel X) from two successive trips during 2009. Fishing effort during the first trip was focused on the western edge of the Norwegian Deeps, with some fishing also in the region of the Long Hole seasonal closure. During that first trip, vessel X fished (according to its VMS pings) in an area which became RTC number 1 (for 2009) during the following week (Figure 6a). Although it cannot be assumed that it was a report from vessel X that triggered the closure, it can be concluded that vessel X was operating in that area. The VMS data from the same vessel's next trip show that fishing was concentrated in the Shetland area (Figure 6b). The mean RCII by fishing ping from the first trip was 0.509, whereas that from the second trip was 0.378. The median distance between trips was 339 km, so, in summary, vessel X was fishing in an area that was subsequently closed. It moved a considerable distance on its next trip and fished in an area which (according to the RCII) was less important for cod.

Without consulting the skipper concerned (if indeed he could recall the trips), the precise reasons for this move cannot be known. There may have been many good reasons other than the closure for the shift in fishing area. However, such comparisons can be used to characterize the changes in fishing areas around the closing or reopening times of RTCs.

Figure 7 summarizes two quantities for all 403 Scottish vessels in the available VMS database that were observed to move away from RTCs following closure (case A): the difference in RCII between the trip preceding the closure and the trip following it (left panels), and the distance moved between the two trips (right panels). The results are presented here as histograms covering each quarter (Q1–Q4) in 2009. The mean RCII difference was negative (meaning that vessels moved away from cod following a

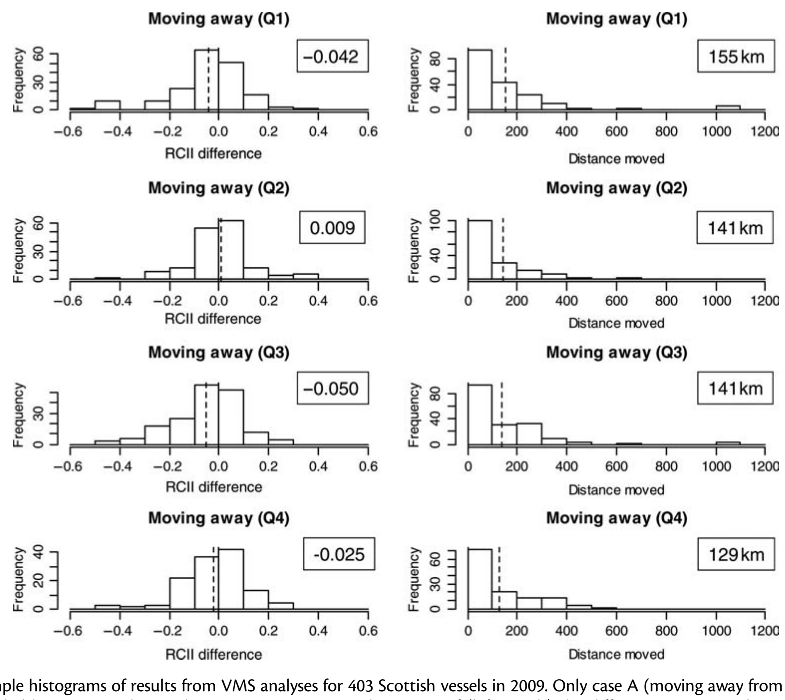

Figure 7. Example histograms of results from VMS analyses for 403 Scottish vessels in 2009. Only case A (moving away from an area after it is closed) is included here. Pre- and post-closure trips are compared in terms of (left panels) the difference in mean relative cod importance index for fishing pings, and (right panels) the distance moved (km). The four quarters of the year (Q1–Q4) are presented separately. The dashed vertical lines and the boxed numbers show the means.

closure) for three of the four quarters of the year, and the distances between trips was greatest during the first quarter.

The mean RCII difference does not in itself indicate whether the movement away from cod was statistically significant. Table 1 summarizes the results of *t*-tests for whether the mean RCII difference was significantly different from zero, for the whole year and for each quarter of 2009. In addition to the results covered in Figure 7, Table 1 also considers those cases in which vessels fished in RTCs while they were closed (case B) and moved back into RTCs after reopening (case C). Over the year as a whole, there was statistically significant (at the 95% level) movement away from cod following RTCs. Significant negative mean RCII differences can be seen in the first, third, and fourth quarters. The positive mean RCII difference in the second quarter could have indicated movement towards cod, and indeed anecdotal evidence from the industry suggests that this may have happened following concerns over catch-composition rules. However, the Q2 value is not significantly different from zero, so firm conclusions cannot be drawn. In terms of what can be determined for case A (moving away from RTCs after closure), it would appear that the movements were generally away from cod. This also holds for case B (fishing in RTCs during closures), although there are few records in this category (only 16.1% of all RTC interactions in 2009) and they are likely to have arisen from vessels which were not fully subject to the RTC scheme. The fishing areas of vessels in the Conservation Credits scheme are closely monitored, and there are strong disincentives to fishing in RTCs. There is significant evidence for an increased RCII when vessels return to RTCs after reopening (case C), overall and for all quarters except the first. These results suggest that RTCs encourage vessels to move away from cod-important areas when they are closed, but do not necessarily discourage renewed fishing on cod when they are reopened.

Table 1. Differences between mean relative cod importance (density) index values for pre- and post-closure trips of Scottish trawlers, for the whole of 2009 and for each quarter thereof (Q1–Q4), and for each of the three cases (see text for details).

Period	Before (case A)	During (case B)	After (case C)
2009	−0.028* ($p < 0.001$)	−0.033* ($p < 0.001$)	0.035* ($p < 0.001$)
Q1	−0.042* ($p < 0.001$)	−0.042 ($p = 0.169$)	0.005 ($p = 0.774$)
Q2	0.009 ($p = 0.411$)	0.000 ($p = 0.982$)	0.026* ($p = 0.009$)
Q3	−0.050* ($p < 0.001$)	−0.081* ($p < 0.001$)	0.050* ($p < 0.001$)
Q4	−0.025* ($p = 0.031$)	−0.024 ($p = 0.155$)	0.051* ($p = 0.001$)

p-values of pairwise Student's *t*-tests carried out to determine whether the values are statistically different from zero are given in parenthesis: significant differences (at the 95% level) are shown by an asterisk.

Table 2. Means of the median distances (km) moved by Scottish trawlers between consecutive trips around closure periods for cod, for the whole of 2009, for each quarter thereof (Q1–Q4), and for the three cases (see text for details).

Period	Before (case A)	During (case B)	After (case C)
2009	142.6*	164.5*	120.7*
Q1	155.2*	154.5	76.5
Q2	141.2	206.1	129.6*
Q3	140.5*	151.4*	118.1*
Q4	129.4*	114.1	135.1*

Cases and quarters for which relative cod importance indices between fishing grounds were significantly different at the 95% level (Table 1) are marked by an asterisk.

Finally, Table 2 reports the means of the distances moved between consecutive trips during 2009 and each quarter thereof, and for each case (A, B, and C). On average, vessels moved further when displaced away from closing areas (case A) than when moving back into reopening areas (case C), which may indicate more deliberate efforts to change the fishing area immediately following a closure. The distance moved following closures (case A) decreased through the year, whereas that following reopening (case C) tended to increase, so that by the fourth quarter, the mean case C distance was actually greater than the mean case A distance.

Conclusions

VMS data have been used in previous studies of the effects of closed areas, but have tended to focus on such aspects as descriptions and models of effort distribution near closures (e.g. Murawski *et al.*, 2005), or the potential impacts of effort redistribution from large, permanently closed areas (e.g. Dinmore *et al.*, 2003). We have considered a rather different problem and have used VMS data and an estimated spatio-temporal RCII to evaluate whether vessels moved away from cod-important areas following the imposition of RTCs in 2009. The results suggest that some avoidance of cod-rich areas following closures did indeed transpire in the first, third, and fourth quarters of that year, but no firm conclusions can be drawn about the second quarter. It would also appear that there was some movement back towards cod-rich areas following the reopening of RTCs. Consequently, we suggest that the RTCs in 2009 did reduce overall cod mortality while they were closed, but that they may not have had any longer-lasting effect on cod exploitation patterns.

However, there are several caveats with the analysis that must be borne in mind. The RCII is at an early stage of development and may not be sufficiently detailed to permit robust evaluations of fleet behaviour at the scale of the small RTCs implemented in 2009. The use of three separate smoothing operations is rather cumbersome, and the spatial scale of the results is perhaps too broad for purpose. We note also that the resultant monthly RCII is deterministic, and does not account for model uncertainty. However, the results reported in this paper do concur with what would have been expected given our experience of survey data and the fishing industry, so we suggest that the method presented here is fit for purpose for the time being.

The patchiness of research-survey and discard-observation data suggests that the RCII should be considered as a minimum estimate of cod abundance, although firm conclusions on this hypothesis are not yet possible. Model-based methods to generate spatio-temporal distributions for cod and other species, taking account of uncertainty and additional information such as depth, are currently being developed, although these will only ever be as good as the data on which they are based. We have assumed in this paper that the data are fully representative, and of course this is open to debate. VMS pings of 2 h may have insufficient resolution to track fishing activities, and the assumed relationship between vessel speed and fishing operations may not apply universally.

Equally importantly, for reasons of tractability we have limited our analysis to those vessels observed to be fishing in the area of RTCs that were subsequently closed (case A), or while closed (case B), or after reopening (case C). We did not attempt to draw any conclusions about the rest of the fleet, which may also have changed behaviour as the result of RTCs, although we cannot tell yet whether this did or did not benefit the cod stock. Moreover, we cannot yet determine whether the movements of the evaluated vessels were unusual. Vessel X (Figure 6) may have intended to fish around Shetland on that second trip anyway, regardless of the implementation of a closure. To address this issue, it will be necessary to track the fishing patterns of specific vessels for longer than a single year, to improve the estimation of cod distribution (and extend it to other relevant species), and to investigate the socio-economic factors that determine the underlying drivers behind changes in fishing location.

This paper should be viewed, therefore, as a first step in an ongoing analysis. The conclusion that vessels generally moved away from cod following the RTCs in 2009 is robust, given the information used and the assumptions made, but should not necessarily be considered as the final result.

Acknowledgements

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And finally, I present two works by Needle and Gurney, which (although unpublished) were very influential in the development of this thesis. Many thanks, Bill.

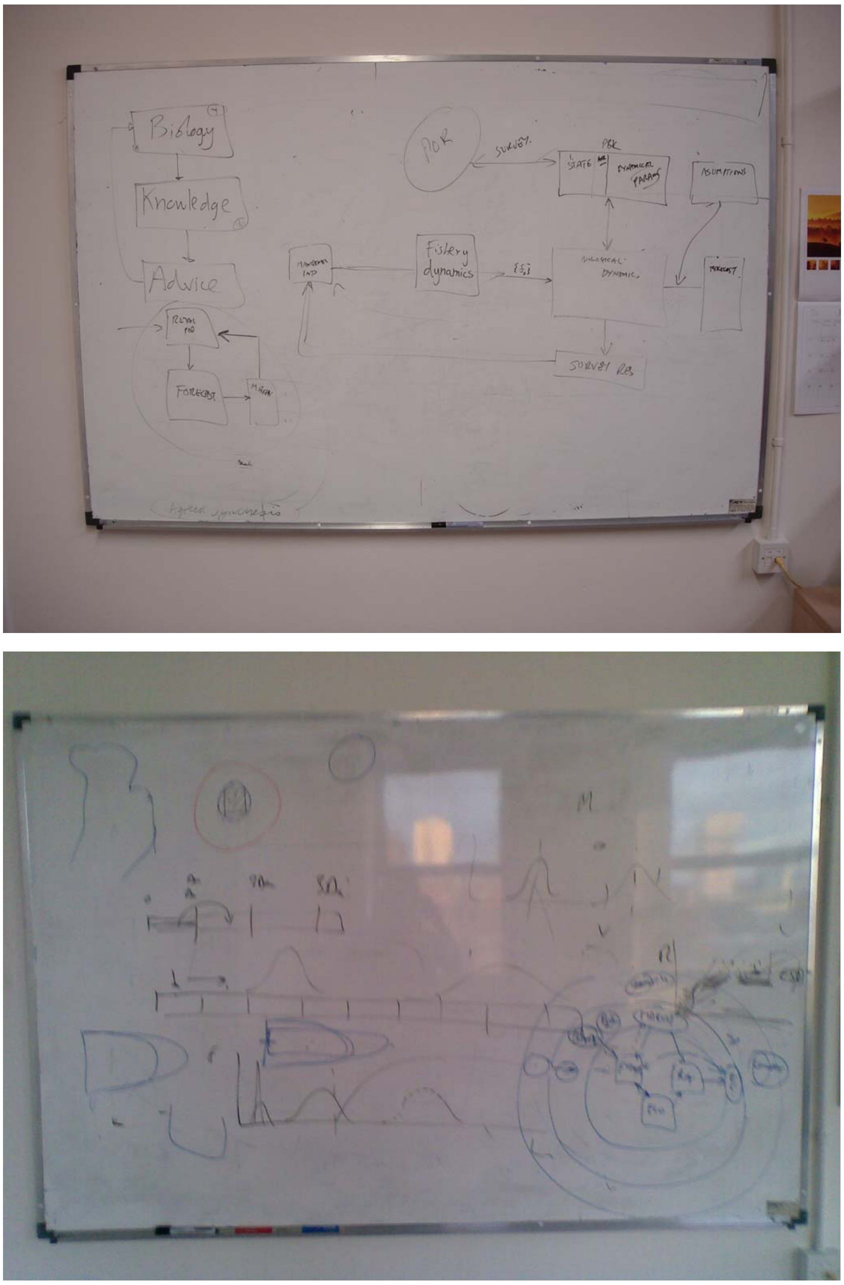

Figure 22.3: Professor Bill Gurney's whiteboard at the University of Strathclyde, Glasgow: February (top) and November (bottom) 2008.

Chapter VII

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