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The Development of a Spatially Dynamic Model to Evaluate Management Scenarios in a Scallop Fishery

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The Development of a Spatially Dynamic Model to Evaluate Management Scenarios in a Scallop Fishery

PRIFYSGOL BANGOR UNIVERSITY

A thesis submitted in fulfilment of the degree of Doctor of Philosophy

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PhD Summary

Fisher behaviour remains a key source of uncertainty in fisheries management. Failing to account for the behavioural response of fishers can lead to unexpected or unintended consequences of management; our understanding of fisher behaviour, as well as our ability to translate this understanding into predictive management models, is underdeveloped. This thesis aimed to develop an individual-based model (IBM) that could be used by fishers and managers to evaluate the impacts of management scenarios in the Isle of Man scallop fishery.

Questionnaire interview data and a conjoint analysis were used to understand fishing behaviour and to generate realistic parameters to input to an IBM of fishing activity. Vessel monitoring system (VMS) and logbook data were also analysed to inform the model development, and to provide the data against which the model could be validated. There is increasing interest in using automatic identification system (AIS) as an alternative to VMS when investigating fishing activity, so a comparison of AIS and VMS data was presented, highlighting substantial gaps in the coverage of AIS data.

By using simple foraging decision rules, parameterised by questionnaire data, it was possible to build an IBM that could reproduce patterns seen in the Isle of Man scallop fishery with reasonable similarity. Comparing multiple submodels of fishing behaviour provided insights into predicting fishing activity, and identified the most structurally realistic models. It illustrated the importance of incorporating random behaviour in a model design, potentially to account for social aspects of fishing decisions that are more difficult to quantify. It also demonstrated that predicting responses to management by modelling fishers as optimal foragers that act in an economically rational manner may overestimate the capacity of the fleet to compensate for restrictions such as closed areas, and underestimate the fishing footprint. Fishery systems may be too complex to distil to a single simple and 'accurate' model, but having a suite of models that together give a reasonable representation of the fishery could allow the range of likely impacts of management to be better considered.

This thesis demonstrates the value of individual-based modelling for both understanding fisher behaviour and predicting the outcomes of management. It has also provided strong evidence to support the use of questionnaire interview data in modelling fishing activity. Comprehensively documenting the stages of model development provided a transparent model validation which would enable managers to make informed decisions about how to apply such a model. Using an IBM to predict the response of fishers to management could facilitate more informed compromises between management objectives, and reduce uncertainty in fisheries management.

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*value of scallops landed per trip, and blue histogram of answers to 'What is the minimum viable catch for a trip? Values are scaled from zero to one for confidentiality. **D)** Grey histogram of trip length in hours at sea from VMS data, and blue histogram of answers to 'How long would you normally fish for?'*

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Glossary

ABC	Approximate Bayesian Computation
ABM	Agent Based Model
ACBC	Adaptive Choice Based Conjoint
AIC	Akaike's Information Criterion
AIS	Automatic Identification System
ANOVA	Analysis of Variance
ASP	Amnesiac Shellfish Poisoning
Between patch decision	The decision of if, and where, to change fishing patch.
CHI	Fishing ground referred to as 'Chickens'
cHs	Cubic Hermite Spline
CPF	Central Place Foraging
CPUE	Catch Per Unit Effort (e.g. kg caught per hour of fishing).
CPUE (per dredge hour)	Amount caught by one dredge on one hour, and therefore comparable across vessels of different sizes.
DEFA	Department of Environment Food and Agriculture, Isle of Man Government.
Departure distance	The distance a vessel travels from its departure port to the mean coordinates of its fishing activity.
Dredge hour	An hour towing one dredge, and is therefore comparable across all vessels.
EBAFM	Ecosystem based approach to fisheries management
EBFM	Ecosystem based fisheries management
EC	European Commission
EDG	Fishing ground referred to as 'East Douglas'
EFF	Efficient Fisher; a category of fisher determined from the conjoint analysis
External Vessel	A vessel not from the Isle of Man
FAO	Food and Agriculture Organisation of the United Nations
FK	Fishers' Knowledge
GES	Good Ecological Status
GIS	Geographic Information System
GLM	General Linear Model
GLMM	Generalised Linear Mixed Effects Model
GPS	Global Positioning System
GUT	Giving Up Threshold. A catch rate at which a forager or fisherman would change location
HB	Hierarchical Bayes
IBM	Individual-based Model
ICES	International Council for the Exploration of the Sea
IFD	Ideal Free Distribution
IOM	Isle of Man
LK	Local Knowledge
Manx	From the Isle of Man
Meat yield	The proportion of white adductor muscle in a scallop; this is the part most commonly eaten, i.e. higher meat yield is more valuable.
MLS	Minimum Landing Size
Model structure	The combination of submodels used in a simulation
MSFD	Marine Strategy Framework Directive

MVT	Marginal Value Theorem
nm	Nautical miles
ODD	Overview, Design Concepts, and Details
OFT	Optimal foraging theory
Patch choice decision	The initial decision of which patch to travel to and start fishing in at the start of a fishing trip.
PCA	Principal Components Analysis
POA	Fishing ground referred to as 'Point of Ayre'
POM	Pattern Oriented Modelling
PPUE	Profit Per Unit Effort
QLM	Quality Maximiser; a category of fisher determined from the conjoint analysis
QTM	Quantity Maximiser; a category of fisher determined from the conjoint analysis
REML	Restricted Maximum Likelihood
Return decision	The decision of if, and when, to return to port.
Roe/gonad status	The reproductive status of a scallop; full roe is more valuable.
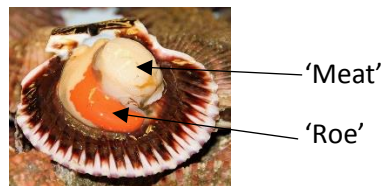
SAR	Swept Area Ratio
SBFM	Systems based fisheries management
sd	Standard deviation
submodel	A behavioural rule in the IBM (e.g. returning to port at curfew, or after 'good takings')
SL	Straight line
TAC	Total Allowable Catch
TAR	Fishing ground referred to as 'Targets'
VCU	Vessel Capacity Unit
VIF	Variance Inflation Factor
VMS	Vessel Monitoring System
VPUE	Value Per Unit Effort
VPUF	Value Per Unit of Fuel used (i.e. £'s of scallop caught per litre of fuel used)

CHAPTER 1: Introduction

1.1. Fisheries are important for global food security

The world population is expected to reach nine billion by 2050. This represents a significant challenge in terms of food security, in the context of climate change, economic, financial, and political uncertainty, and growing competition for natural resources. In 2013, fish accounted for about 6.7% of all protein consumed, and provided more than 3.1 billion people with almost 20% of their average per capita intake of animal protein. However, 31% of global fish stocks have been estimated as fished at biologically unsustainable levels, and are therefore considered overfished, which poses a threat to food security (FAO, 2016).

There are, however, two somewhat diverging views of the status and future of the world's fisheries among the scientific community (Hilborn, 2007a). Some believe fisheries management is failing globally and predict dire consequences for the world's oceans (Myers and Worm, 2003; Pauly *et al.*, 1998; Worm *et al.*, 2006, 2009). Others have a less alarmist view, and argue that it is a *lack* of management that causes depleted stocks rather than a failure of management itself, believing that we can learn from fisheries that have been successfully managed to improve the status of other overfished stocks (Beddington *et al.*, 2007; Hilborn, 2007a; Hilborn and Ovando, 2014). Nevertheless, it is agreed that overfishing can cause negative ecological, social, and economic consequences (FAO, 2016; Kaiser *et al.*, 2006; Myers *et al.*, 2000; Worm *et al.*, 2009). There is a need to strengthen fisheries governance to deal with increasing pressures, in order to ensure sustainable marine fisheries that can provide food security for future generations, whilst meeting the common goals of environmental protection and ecosystem and biodiversity conservation.

1.2. Managing Fisheries is Managing People

Despite sharing a common interest in maintaining sustainable fisheries (Jennings *et al.*, 2014), different groups of people (e.g. fishers, governments, NGOs, scientists) may be measuring sustainability against different objectives, measures, and definitions (Hilborn *et al.*, 2015). There is more often a focus on ecological or environmental sustainability; but neither environmental nor socio-economic objectives can be successfully met by focussing only on the state of the resource (Fulton *et al.*, 2011). Failing to account for social and economic impacts can lead to a lack of compliance which undermines management (Peterson and Stead, 2011), and incentives and feedbacks can lead to behavioural responses that result in unintended consequences (Hilborn *et al.*, 2004; Pascoe and Mardle, 2005). The sustainability of seafood production for future generations is

dependent on the success or failure of management institutions to effectively control and adjust the fishing pressure to appropriate levels (Hilborn *et al.*, 2015).

Hilborn (2007) stated "managing fisheries is managing people", and stressed the importance of understanding fishermen's motivations, and the interaction between their objectives and the incentives created by any management option. This notion has been expressed and reiterated by many fishery scientists over the decades (Bucaram *et al.*, 2013; Fulton *et al.*, 2011; Hallwass *et al.*, 2013; Hart, 2003; Wilen, 1979, 2006), yet a generation of 'command and control' fishing policies, where top down legislative measures prescribe where and when fishermen can fish, has somewhat failed to take account of the societal and economic dimensions of fisheries (Bacalso *et al.*, 2013; Bucaram *et al.*, 2013; Bucaram and Hearn, 2014; Fulton *et al.*, 2011). Despite its acceptance in the academic world, it is not yet the norm for fisheries management to explicitly incorporate social and economic dimensions, including fisher behaviour. Failing to account for social and economic outcomes of management has potentially contributed to management failures (Hart, 2003; Hilborn, 1985; Wilen, 2006).

1.3. PhD Rationale

This PhD aimed to address a significant source of uncertainty in fisheries management, namely, the behavioural response of fishermen to management (Branch *et al.*, 2006; Fulton *et al.*, 2011; Hart, 2003; van Putten *et al.*, 2012). Fishers do not always respond to management as expected, which can lead to unintended consequences of management (Dinmore *et al.*, 2003). For example, management can unintentionally displace effort into areas that were previously unfished for several years (Piet *et al.*, 2007), into areas of sensitive habitats (Nilsson and Ziegler, 2007), or lead to an increase in the economic cost of fishing (Hilborn *et al.*, 2004; Smith *et al.*, 2010). Understanding more about how fishers might respond to management, in terms of adaptive and compensatory behaviour, would reduce some of the uncertainty surrounding fisheries management, and could reduce unintended consequences of management. Despite being recognised as important in determining the outcome of management, both our understanding of fisher behaviour, and the translation of this understanding into predictive management models is underdeveloped (van Putten *et al.*, 2012).There is a growing need for comprehensive fisheries models that incorporate a range of social, economic, and ecosystem interactions, and are capable of forecasting future scenarios, and predicting potential impacts of, and responses to, management strategies (Fulton *et al.*, 2011; Reeves *et al.*, 2009; Wilen *et al.*, 2002). The development of simulation tools, in which the potential environmental and economic consequences of different management scenarios could be explored,

could allow a more holistic approach to fisheries management. For example, when considering a potential new closed area, it could answer questions such as: Where would the fishing activity be displaced to? What would the environmental impact of this shift be, in terms of the change in fishing footprint? And what would the economic impact be for the fishermen? Whilst managers do not always understand fishers' motivations and responses to management, fishers also do not always understand how or why managers make certain decisions, which can lead to conflict. Developing a simulation tool that could address the above types of questions could allow scientists, managers, and fishers to understand more about how management could affect the fishery, from both an environmental and an economic perspective. It could also provide fishers with access to a scientific tool to assess alternative management options that minimise economic losses, whilst achieving biological or environmental targets. This PhD was the first step in developing such a management simulation model for a data rich scallop fishery in the Isle of Man.

1.4. The importance of incorporating fisher behaviour into management.

Fisheries management aims to achieve a balance between resource exploitation and environmental protection; it should maintain productive and profitable fisheries for food and employment security, while ensuring any negative ecological and environmental impacts are minimised (Beddington *et al.*, 2007; Kaiser *et al.*, 2016; Worm *et al.*, 2009). Ecosystem based fisheries management (EBFM) is increasingly recognised as a more holistic integrated approach to fisheries management (Pikitch *et al.*, 2004). EBFM emerged in response to the shortcomings of focussing on a single target species; by focussing on a single species, other ecosystem components, such as the species' predators, prey, or habitats, are often overlooked. As well as considering ecosystem effects, EBFM also aims to take a broader view of fisheries management, to maintain long-term socio-economic benefits, in balance with environmental protection (Pikitch *et al.*, 2004).

In systems based fisheries management (SBFM) the social-ecological system is considered as a whole, with feedbacks between the ecological and social-economic systems explicitly considered. Single species management can be criticised as biased to one species, failing to account for the ecosystem impacts, whereas EBFM can be considered biased towards the ecosystem, failing to account for the complex coupling of social ecological systems (Fulton *et al.*, 2011; van Putten *et al.*, 2012). SBFM recognises it is not simply fishing patterns that influence the fishery ecosystem, but a series of complex interactions between ecosystems and social, political and economic factors that drive fishery dynamics (Hilborn, 2007b; Plagányi *et al.*, 2014). SBFM aims to take account of how governance structures, such as regulations, incentives, or stakeholder engagement processes, can

influence fishery dynamics and resulting environmental footprints and socioeconomic impacts (Burgess *et al.*, 2017).

Nevertheless, fishery systems are complex, and understanding all of the interacting environmental, social, and economic influences on fisheries dynamics, and thus management, is not simple. In particular, there are two types of uncertainty relevant to fisheries management; scientific uncertainty (Ralston *et al.*, 2011) and management or implementation uncertainty (Fulton *et al.*, 2011). Scientific uncertainty assumes that fishers respond as expected, and the uncertainty is concerned more with the stock models, e.g. when the actual catch equals the total allowable catch, but there is uncertainty in the scientific stock models. Management uncertainty considers the uncertainty in the fishing pattern resulting from a management scenario, e.g. the behavioural response of fishermen. Management uncertainty is less understood, but understanding this could be critical to successful fisheries management, through reducing unintended consequences of the management actions that are implemented (Fulton et al., 2011). The adoption of SBFM is likely to require significant advances in our understanding of fisheries systems, including both the human and ecological elements of a fishery, and the complex interactions and feedbacks between the two, in particular to reduce management uncertainty (Burgess *et al.*, 2017).

There has been increasing recognition that it is important to understand fisher behaviour to achieve successful management outcomes (Bacalso *et al.*, 2013; Charles, 1995; Girardin *et al.*, 2016; Gordon, 1953; Hallwass *et al.*, 2013; Hilborn, 2007b; Hutton *et al.*, 2004; Little *et al.*, 2004; Marchal *et al.*, 2007; Murray *et al.*, 2011; Salas and Gaertner, 2004; Wilen *et al.*, 2002), with increasingly more studies investigating fishery behaviour, perhaps led by a move towards management measures that aim to modify the behaviour of fishers, and an increase in computing power (van Putten *et al.*, 2012). Failing to account for the behavioural response of fishers can lead to unintended consequences of management, and even produce negative environmental, economic, or social effects (Hilborn *et al.*, 2004; Pascoe and Mardle, 2005). For example, in 2001 the 'cod box' excluded the North Sea beam trawl fleet to protect spawning aggregations of cod. However, to compensate for this exclusion, fishers moved to a previously unfished area, resulting in a long term negative impact (Dinmore *et al.*, 2003). A failure or inability to account for the behavioural response of fishers in this case led to unintended negative consequences for the benthic ecosystem in a previously unfished area of the seabed. To implement effective fisheries management, we must be confident that fishers will respond to the management actions as intended (Dinmore *et al.*, 2003), and that expected reductions in effort or mortality will be realised (Daw, 2008).

The incorporation of fisher behaviour into fisheries management can be considered from two related perspectives; the predicted level of compliance or acceptance associated with management actions, and the compensatory response of fishers and therefore efficacy of management actions, both of which would provide insights into the potential success of management strategies. Hallwass et al. (2013) suggested that compliance and acceptance could be estimated as inversely proportional to catch decline; the lower the impact on catches, the more likely the management option would be to be accepted. Nevertheless, we must first understand what the impacts on catches may be. Modelling a reduction in available biomass by simply removing a proportion of the total catch neglects the possibility of compensatory behaviour, and assumes proportional redistribution of effort to other fishing areas (Dowling *et al.*, 2012). Some management measures may be more restrictive to fishermen, whereas others may allow a simple alternative fishing strategy to prevent financial loss. In fisheries with a higher diversity of gear, habitats, target species, and alternative income, fishers may be able to absorb a loss in fishing income by switching to another source of revenue (either non-fisheries or through changing fishing method/location), and therefore be more accepting of a greater variety of management options (Cambiè *et al.*, 2017). Nevertheless, this displacement of effort could impact on another fishery or ecosystem. The response of fishers is an important determinant in management success. For example, what appears to be a simple method to reduce fishing pressure, such as reducing the number of active vessels, may not necessarily reduce the fishing mortality (Murray *et al.*, 2011), and nearshore management actions have been demonstrated to drive the fishery further out to sea, resulting in no substantial reduction in net catches, but a potential increase in the cost of fishing (Daw, 2008). Unanticipated behavioural responses from fishers can therefore reduce the efficacy of management strategies.

Environmental policies are generally developed centrally, based on the assumption that resource users will respond homogenously to management actions (Gelcich *et al.*, 2005). However, as demonstrated in farmed systems, the adoption of top down environmental policy, such as agri-environment schemes, varies considerably with age, education, attitude to risk, and personality (Greiner *et al.*, 2009; Sheikh *et al.*, 2003; Vanslembrouck *et al.*, 2002). Both farmers and fishers derive their livelihood from the environment, and subsequently, studies have shown that fishers' responses to policies can also depend on attitudes, personalities, and livelihoods (Gelcich *et al.*, 2005). This suggests that responses may vary between groups and among individuals, meaning a thorough understanding of the individual behaviours in the system is required to make predictions about responses of individuals to management actions (Gelcich *et al.*, 2005).

1.5. Fisher behaviour within the framework of Optimal Foraging Theory

Fishers and exploited fish/shellfish populations can be considered analogous to animal predator-prey systems, in which fishers are predators competing for a particular prey resource. However, whilst substantial research has been conducted on the exploited 'prey' in fisheries, the behaviours and population dynamics of the 'predators' (fishers) have received less attention (van Putten *et al.*, 2012). This imbalance in fisheries systems leads us to understand only half of a coupled system. A number of authors have demonstrated Optimal Foraging Theory (OFT) (MacArthur and Pianka, 1966) to be a suitable framework for investigating fisher behaviour (Begossi, 1992; Begossi *et al.*, 2009; de Oliveira and Begossi, 2011; Lee *et al.*, 2014; Sosis, 2002). Optimal foraging theory states that individuals aim to maximise their net energy intake over time (analogous to catches or profit for a fisher); there are several models under the umbrella of OFT relevant to modelling fishers (Figure 1.1).
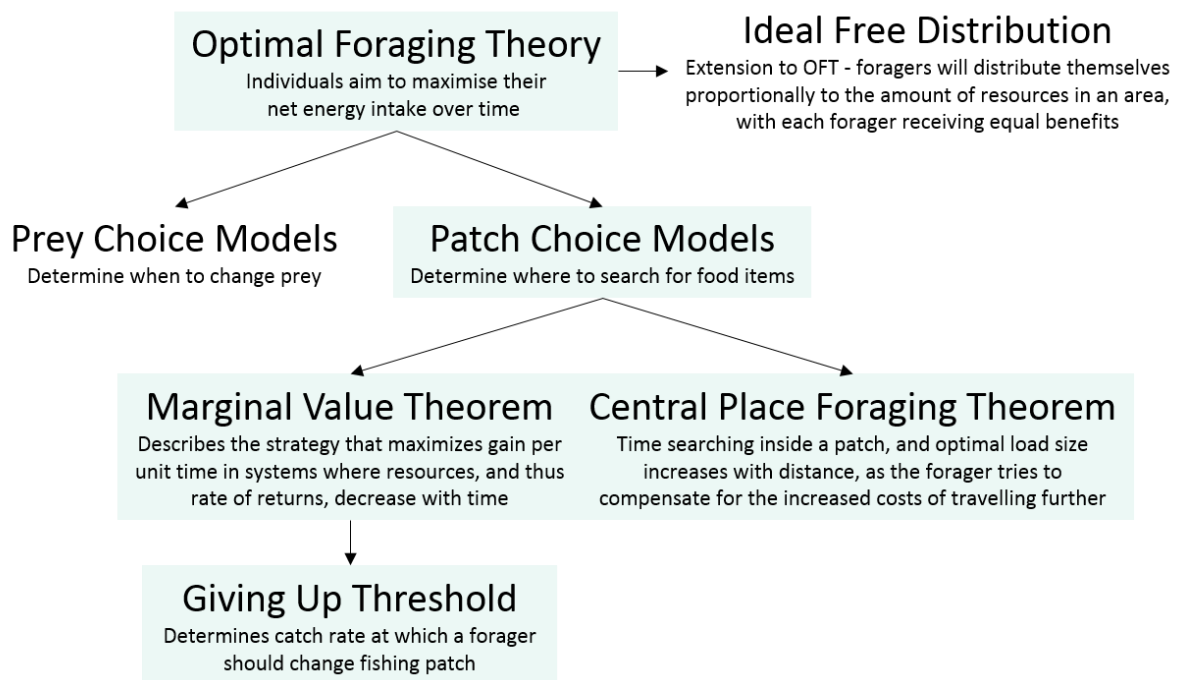
Figure 1.1 Optimal Foraging Models. Blue shaded boxes indicate those explored further during the PhD

An extension to OFT incorporates the Ideal Free Distribution (IFD; Fretwell and Lucas, 1969), which predicts that foragers will distribute themselves proportionally to the amount of resources in an area, with each forager receiving equal benefits. Therefore, more foragers will be present in resource-rich patches, but the overall return rate will be equal between foragers. The IFD has been demonstrated to offer a good estimation of the distribution of fishers moving between distinct

foraging sites (Gillis, 2001, 2003; Voges *et al.*, 2005) but significant deviations from this prediction also have been found (Abernethy *et al.*, 2007).

Other theoretical models relevant to fisheries fall under the framework of OFT: Patch Choice Models determine where to search for food items; Marginal Value Theorem determines how long to search for items; and Central Place Theorem predicts foraging levels given the distance travelled (Charnov, 1976; MacArthur and Pianka, 1966; Orians and Pearson, 1979; Figure 1.1). Marginal Value Theorem (MVT; Charnov, 1976) has been used to predict how long fishers should stay in a fishing ground, with some success, although fishers have been shown to operate sub-optimally, staying longer than MVT predicts is economically optimal (Begossi, 1992). De Oliveira and Begossi (2011) have also demonstrated that the predictions of the Central Place Foraging Theorem (CPF) hold true; time searching inside a patch, and optimal load size (i.e. catch size) increases with distance, as the forager tries to compensate for the increased costs of travelling further. Prey Choice Models determine when a forager should change their target prey species. In single-species fisheries there may not be an alternative prey or target species; however, it could also be considered analogous to sourcing alternative income. The level of off sector pluriactivity has been shown to be a strong determinant in predicting responses to management (Gelcich *et al.*, 2005) but the ability to change income source will vary between individuals within and between fisheries (Cambiè *et al.*, 2017).

Under the framework of OFT, according to the MVT, a forager can be expected to use a resource until the energetic cost exceeds the gain (MacArthur and Pianka, 1966); similarly, a fisher could be expected to operate in an area until the perceived benefits of moving to a different location out-weigh the costs. This could be in relation to returning to a patch on subsequent trips, or in moving between patches during a fishing trip. Indeed de Oliveira and Begossi (2011) found that fishers returned more often to grounds where the return rate of the previous trip was higher than the average return for the environment. Griffen (2009) also showed that the use of simple patch leaving rules, based on decision rules according to current consumption rates (c.f. the theory of MVT which has an unrealistic assumption of ideal knowledge of alternate consumption rates), allowed crabs to distribute approximately according to ideal free expectations. The return rate at which a forager decides to change location can be termed the 'giving up threshold' (GUT). In fisheries this could represent a resource density below which it is not economically viable to continue fishing. The GUT may vary between individuals, and may depend on a range of variables, such as economic strategy or spatial preferences, and average stock status across all grounds (i.e. how depleted the resources are).

With regards to predicting fishing behaviour, OFT and associated models are, however, subject to some unrealistic assumptions, namely: foragers have ideal knowledge of resource levels in each patch; foragers are able to move equally between all patches; and foragers have equal competitive abilities. In reality, this would not be the case; fishers may know estimates of resource densities, but cannot know exact values; larger vessels may have greater potential to travel further and more quickly between patches; and larger vessels may out-compete smaller vessels (Rijnsdorp *et al.*, 2008).

Fishers are also often assumed to be perfectly informed rational profit-maximisers (profit maximisation can be considered analogous to optimal foraging), who value future profits less than current profits (Holland, 2008). Indeed an unwillingness or inability to accept short term costs in favour of long term benefits may have contributed to the difficulty in reducing overfishing (Beddington *et al.*, 2007). Nonetheless, in reality, there are likely to be violations to the assumptions of profit maximisation behaviour, but these violations are not well understood in fisheries (Abernethy *et al.*, 2007; Christensen and Raakjær, 2006; Holland, 2008). The economic drivers for each fisher may be influenced by additional social factors, such as safety, comfort and time (Bene and Tewfik, 2001; Cabrera and Defeo, 2001; Salas and Gaertner, 2004). The response of fishers to management actions may be influenced by these social factors (Abernethy *et al.*, 2007). Christensen & Raakjær (2006) found that less than 10% of fishers had a strategy based strongly on profit maximisation. Leisure time is often not considered in fisheries economic models, but can be an important trade-off with fishing for longer and achieving higher profits (Abernethy et al., 2007). Yield- or income-targeting behaviour (Simon, 1955) and loss aversion (Kahneman and Tversky, 1979) could also lead to deviations from profit maximisation; fishers have been shown to exhibit satisficing behaviour, in which profit maximisation is no longer the objective function once a certain level of need or satisfaction has been met (Christensen and Raakjær, 2006; Jager *et al.*, 2000; Salas and Gaertner, 2004). Béné (1996) defined a fisher's strategy to be "the set of decision criteria that link a given fishing behaviour with the objective(s) and constraint(s) that have stimulated such behaviour". To successfully predict the fleet-wide responses to management options we must understand the individual differences in competitive drive and ability of the fishers, as well as their differing economic expectations, incentives and drivers (Bene and Tewfik, 2001; Gelcich *et al.*, 2005). A better understanding of the relative importance of driving factors and motivations per individual would allow insights into how economic strategies differ both within and between fisheries.

Modelling fishermen with an assumption that they act with perfect economic rationality, i.e. always behaving in a way that maximises their income, also implies that they are able to consider all possible options and outcomes and weigh them up before making a decision (i.e. perfect rationality)

(Holland, 2008). In practice, fishers may use simple 'rules of thumb' to decide where to fish, because the time it would take to rationally decide between all possible fishing options would be uneconomical, and they may be better off using a simple rule or 'hunch' to maximise the available fishing time, rather than computing the perfect choice (Gatewood, 1983; Holland, 2008; Tversky and Kahneman, 1974). Fishers also tend to be risk averse and habitual, and are likely to choose the same location to fish out of habit and inertia to change (Eggert and Martinsson, 2004).

1.6. Individual-based modelling of fishing behaviour

Predicting how a system will respond to change (e.g. management in a fishery) is often difficult, due to both a lack of historical data, and the assumption that empirical relationships derived from current conditions will remain the same under future scenarios (Stillman, 2008). A review of 26 papers by Girardin et al., (2016) demonstrated that expected revenue, tradition, and the presence of other vessels positively influenced effort allocation, but choices associated with large costs were avoided (i.e. fishers were risk averse, preferring to maintain a stable income). Nevertheless, the majority of studies investigating fishing behaviour were based on simple, linear, data-driven models (e.g. random utility models), which don't capture complex decision processes, and thus have limited predictive capacity in novel scenarios (Girardin et al., 2016). Individual-based modelling provides a research paradigm that is more flexible and predictive than more statistical models which are only really valid for the environmental conditions under which they were created, and thus have limited predictive capabilities (Evans *et al.*, 2013; Girardin *et al.*, 2016; Grimm and Railsback, 2005). IBMs view systems as having properties that arise from the behavioural traits and interactions of its constituent individuals (DeAngelis and Mooij, 2005). In an IBM of foraging behaviour, individual behavioural rules can be constructed to maximise individual fitness, and then from these individual behaviours the population wide patterns emerge. Individual fitness-maximising behavioural decisions should theoretically stay the same under novel environmental conditions, which means that individuals in an IBM can be expected to respond in a similar way to individuals in real life (Grimm and Railsback, 2005).

In a fishery, it is difficult to quantitatively characterise all of the variables that can influence individuals' motivations and behaviours (e.g., such as gut feeling or intuition), which can be termed 'black box' variables (van Putten et al., 2012). Nevertheless, it is more straightforward to account for a range of deviations from foraging or economic theory in IBMs, as individuals can operate according to more realistic representations of the decision making process, which can also vary between individuals or subsets of the system. IBMs could also give more accurate predictions of the costs of

fishing, because fishing activity is modelled more explicitly, so individual costs can be calculated according to individual effort and power, rather than statistically relating costs to effort (Bastardie et al., 2014). IBMs could help address some of the knowledge gaps in our understanding of fisher behaviour, and allow us to better predict the environmental and economic consequences of management by more realistically accounting for the behavioural response of, and impact on, fishers (Burgess *et al.*, 2017).

IBMs have been used widely in modelling animal populations and predicting their responses to management measures (Durell *et al.*, 2006; Goss-custard *et al.*, 2008; Stillman and Goss-Custard, 2010; Toral *et al.*, 2012; West *et al.*, 2007), often offering realistic predictions that are verified with subsequent direct observational data (Toral *et al.*, 2012). In fisheries, IBMs have been used to show how Individual Transferable Quotas (ITQs) can change spatial patterns of fishing and bycatch levels (Little *et al.*, 2009; Poos *et al.*, 2010; Toft *et al.*, 2011), how fisheries management can affect other sectors such as shipping (McDonald *et al.*, 2008), the importance of understanding compliance (Cabral *et al.*, 2010), the potential consequences of marine reserve placement (Dowling *et al.*, 2012; Moustakas *et al.*, 2006), the energy efficiency of vessels (Bastardie *et al.*, 2010a), and effects of effort displacement on both stock dynamics and economic performance (Bastardie *et al.*, 2014). When considering spatial management measures such as area closures, one advantage over statistical models is that in an IBM effort does not have to be proportionally redistributed (Dowling *et al.*, 2012). For example, vessels may concentrate along the edges of closed areas in response to an actual or perceived 'spill-over' effect (Goñi *et al.*, 2008), known as 'fishing the line' (Kellner *et al.*, 2007).

In current fishery IBMs, profit maximising behaviour is generally assumed, with individuals behaving largely according to optimal foraging theory, in that they forage in patches with the highest expected return. Alternative processes and mechanisms are generally not considered (i.e. one model structure is used, rather than multiple possible structures being tested) (Grimm *et al.*, 2005); there may be different ways to represent processes in a model, some of which might perform better than others. For models to be applied directly to management planning, there must be confidence in the reliability of the model, which means there must be a thorough validation process. Validation of fisheries IBMs has previously been somewhat qualitative, or based on relatively few coarse scale data points (e.g. Dowling *et al.*, 2012; Little *et al.*, 2009), perhaps due to the paucity of appropriate data for validation. A more fine scale validation of the behaviours of vessels in fishery IBMs would lead to a greater confidence in applied model predictions. In addition, comparing different submodel structures of the same system (e.g. choosing where to fish at random compared to where the

highest catch rates are) would increase confidence that not only the outputs of the model are realistic, but that the underlying processes driving the patterns are realistic (Grimm *et al.*, 2005).

IBMs are often validated using pattern oriented modelling (POM; Grimm *et al.*, 1996, 2005), in which the model outputs are compared against a series of characteristic patterns observed at different levels in the system. If a model can simultaneously recreate multiple emergent patterns in a system, one can assume that the behavioural mechanisms of individuals in the model should be somewhat realistic (Grimm *et al.*, 2005). Nevertheless, POM can be considered somewhat qualitative. Approximate Bayesian Computation (ABC) has been demonstrated as an alternative, more quantitative method of model validation (van der Vaart *et al.*, 2015, 2016). In ABC, models can be simultaneously evaluated against numerous values, to either facilitate parameter calibration, or for model selection (van der Vaart *et al.*, 2015). A more detailed discussion of IBM validation and the ABC process is presented in Chapter 6.

1.7. Individual-based modelling and fisher engagement / participation

Models are an important tool for fisheries scientists, as *in situ* experiments to see how fisheries would respond to novel management scenarios are neither feasible nor ethical. Even so, models can be complex, so it is important to be able to effectively communicate them to stakeholders and end users, such as fishers, managers, and decision-makers, to facilitate acceptance and appropriate application of the outputs (Cartwright *et al.*, 2016). Fishers have been shown to have a lack of trust in the scientific evidence that currently sets controls and policy (Rees *et al.*, 2013; Röckmann *et al.*, 2012). They can feel that data collected by scientists does not sufficiently reflect their fishery, leading to inappropriate conclusions (Bergmann *et al.* 2004), and can be sceptical of complex models, being overly critical of model uncertainty, or conversely (but equally problematically) overly trusting of the 'headline' results of a model (Cartwright et al., 2016). This can be further confounded by a bias to either trust or reject a model depending on how well it aligns with pre-conceived ideas of the system (Cartwright et al., 2016). The integration of public participation in science has been demonstrated to address some of the concerns surrounding credibility and uncertainty in fisheries (Voinov and Bousquet, 2010; Yates, 2014). It is increasingly acknowledged that better management decisions can be implemented when stakeholders are engaged in the decision making process, e.g. through participatory modelling (Gelcich *et al.*, 2005; Mackinson *et al.*, 2011; Voinov and Bousquet, 2010). Attitudes, behaviour, and motivations can be influenced by the level of participation in the decision making process (Gelcich *et al.*, 2009; Pita *et al.*, 2010), and direct participation can increase support, interest and legitimacy (Mackinson *et al.*, 2011; Röckmann *et al.*, 2012).

When communicating with non-scientist end users, there are several advantages of IBMs over phenomenological or statistical models, in particular: individuals are simulated, following simple behavioural rules, which is often easier to understand than the behaviour of entire populations; models can appear more realistic, in that they have real-world relevance, often being mapped to real systems, with complexity and heterogeneity included rather than being in simplified averaged forms; and finally user-friendly software packages such as NetLogo allow end users to easily interact with the model, and view simple visualisations (see Cartwright *et al*., 2016 for review). In addition, standardised documentation of IBMs has helped facilitate communication and critical scientific evaluation (Cartwright *et al.*, 2016; Grimm *et al.*, 2010). For example, the 'ODD' (Overview, Design concepts, and Details) protocol for describing IBMs provides a standardised format with which IBMs can be documented (Grimm *et al.*, 2006, 2010).

Participatory modelling could engage fishers in evaluating management strategies, provide a platform for them to influence management decisions using a scientific backing, and potentially increase their support for the most appropriate management strategy. It could also facilitate discussion, and increase scientists' understanding of fisher behaviours and driving motivations, their understanding of management, and their preferences concerning compromises. Engaging fishers in the modelling process can also provide useful information and data for the model development. When parameterising a bird foraging model such as MORPH (Stillman, 2008), extensive effort was required to document model parameters, such as energetic requirements, capabilities, feeding rates, etc. In a fishery, it is possible to simply ask the foragers about these requirements. Collecting data directly from fishermen, which can be termed fishers' knowledge (FK) or local knowledge (LK), can provide useful and reliable information on a fishery system (Leite and Gasalla, 2013; O'Donnell *et al.*, 2012; Shepperson *et al.*, 2014; Teixeira *et al.*, 2013).

1.8. Trawl fisheries are economically important, but can be controversial.

Trawl fisheries (here referring to all bottom towed gear, e.g. beam trawl, otter trawl, towed dredges, and hydraulic dredges) are important for global food production, producing around 16 million tons of food annually. But, like all forms of fishing (and indeed all food production), there is an environmental impact (Kaiser *et al.*, 2016). In trawl fisheries heavy gear is in direct contact with the seabed and so it can physically disturb and cause substantial damage to its associated flora and fauna (Eigaard *et al.*, 2015; Kaiser *et al.*, 2006, 2016). This has led to a negative portrayal in the media in recent years, particularly with scallop dredging, including news articles and a high profile

television series by a celebrity chef (McKie, 2014; Monbiot, 2015; Renton, 2013; www.fishfight.net). Nevertheless, considering their importance both economically and for food security, it is important that we find appropriate management solutions that achieve a balance between fisheries production and environmental protection (Kaiser et al., 2016).

In 2015, UK vessels landed 708,000 tonnes of sea fish, including shellfish, into the UK and abroad, with a value of £775 million; shellfish accounted for 36% of this value (Marine Management Organisation, 2015). In the UK, scallops are mainly fished using bottom towed gear such as dredges and trawls, which can be controversial gears, but the fishery is of considerable importance to the UK economy; scallops landed by UK vessels into the UK totalled £64 million in 2015, making it the second most valuable fishery to the UK fleet, behind the Nephrops fishery at £81 million (Marine Management Organisation, 2015). Management should therefore aim to reduce the environmental impacts and balance these against the economic impacts. A substantial portion of the catch came from the Irish Sea, around the Isle of Man (Figure 1.2).
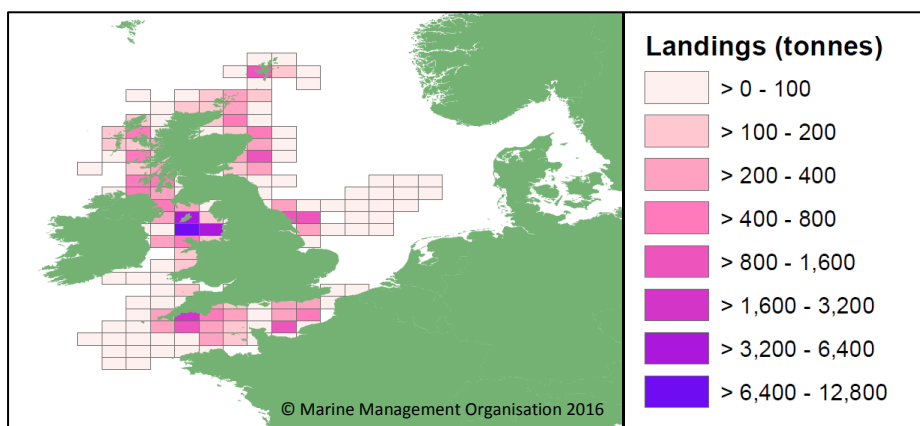
Figure 1.2. Quantity of Scallops landed by UK vessels from each ICES rectangle in 2015 (Marine Management Organisation, 2015)

Scallop fisheries are subject to relatively little active management in the UK, although there are effort restriction (e.g. seasonal closures, curfews, limits to the number of dredges permitted, restrictive licencing), gear restrictions, and a minimum landings size, the details of which vary around the UK. Understanding the fishing footprint is a fundamental piece of information required to manage any fishery. It is especially important with potentially more damaging forms of fishing such as scallop dredging, particularly as the impact varies according to the habitat in which it occurs (Kaiser *et al.*, 2006). Scallops are found in a range of habitats, from sheltered shallow inshore areas, to deeper seas, to areas of high natural disturbance from waves or tidal currents; areas of high natural disturbance are less likely to be significantly impacted by dredging than areas of low natural

disturbance (Kaiser et al., 2006). It is thus important to have a good understanding of what habitats and environments scallop dredging occurs in to fully understand the impacts (Kaiser *et al.*, 2016). In addition, the environmental consequences of displacing a more damaging form of fishing from a more resilient to a more sensitive habitat may be higher, making it even more important to understand the potential displacement of scallop dredging effort following management.

In Europe, vessels over 12m in length must carry a vessel monitoring system (VMS) which transmits location data that can be used to monitor and analysis fishing activity (EC, 2009). VMS data provides a spatial location, heading and speed of individually identified vessels at roughly 2 hourly temporal frequency. It does not provide information on the activity of a vessel when a poll is recorded (i.e. if it is fishing or not), but this can be inferred from the speed of the vessel (Lee *et al.*, 2010). Vessels also submit logbook records of their catches, which can be linked to the VMS data using vessel ID and date, resulting in spatially resolved catch records. Using VMS and logbook data to investigate fishing activity has become a field of its own (Bastardie *et al.*, 2010b; Hintzen *et al.*, 2012; Lambert *et al.*, 2012; Lee *et al.*, 2010; Murray *et al.*, 2013). Nevertheless, VMS data is commercially sensitive, and as a result confidentiality issues have threatened the utility of such data for scientific research (Hinz *et al.*, 2013). The data is available at relatively low temporal resolutions (2 hourly polls) which may fail to accurately represent fishing activity at the scale required for fisheries management, particularly with fisheries in which vessels make short tows and tight turns, such as with scallop dredging (Lambert *et al.*, 2012). Automatic identification system (AIS) data could be a higher resolution alternative to VMS data, but there are concerns with data coverage (Mccauley *et al.*, 2016; Natale *et al.*, 2015; Russo *et al.*, 2016). Despite the limitations of VMS data, it is increasingly commonly used to investigate fishing footprints and is becoming a vital tool in the fisheries scientists' toolbox. A more in-depth discussion of the benefits and drawbacks of the two data sources is provided in Chapter 4.

In the Isle of Man, all vessels targeting scallops must carry a VMS regardless of their size, and they are also required to submit a logbook record of their landings. This means that there is complete data coverage of fishing activity within the 12 nautical mile (nm) Isle of Man territorial Sea. In addition, it is a relatively small, simple fishery, with vessels targeting a stationary resource, and making mainly single day trips. This makes it an ideal candidate system to develop a simple, comprehensively validated model, to develop our understanding of predicting fishing behaviour, and to create a flexible modelling framework that could be extended to more complex fisheries.

1.9. PhD Aims and Objectives

The overall aim of this PhD was to create an IBM of fishing activity in the Isle of Man scallop fishery, capable of predicting the displacement of effort following spatial closures. The aim was to parameterise the IBM using vessel monitoring system and logbook data, as well as questionnaire interview data collected from fishermen to ensure that realistic parameters were input to the model. Importantly, having complete VMS and logbook data coverage of the fishery meant that the model could be comprehensively validated to provide confidence in the model predictions. As VMS data is subject to some caveats, such as relatively low temporal resolution, a comparison was also made between lower resolution VMS and higher resolution AIS data.

The specific objectives were:

- To characterise scallop fishing activity in the Isle of Man scallop fishery, using vessel monitoring system and logbook data.
- To further our understanding of scallop fishing behaviour in the Isle of Man through questionnaire interviews
  - How do fishers decide when to fish?
  - How do fishers decide where to fish?
  - Do all fishers make these decisions in the same way?
- To compare fishing activity derived from both VMS and AIS data, exploring the idea that AIS could offer a higher resolution alternative to VMS data.
- To develop an individual-based model of scallop fishing activity in the Isle of Man, parameterised with interview data collected from fishers.
- To validate the IBM using VMS and logbook data to see if the IBM can predict patterns seen in various environmental and economic values (e.g. scallop landings, spatial distribution of effort, costs to fishermen).
- To compare different submodels of fishing behavioural rules, to determine which gives the most realistic representation of fishing activity.
- To create a simulation tool that can predict the response of fishermen to closed areas in the Isle of Man scallop fishery outlining the potential impacts on the fishing footprint and fisheries landings.

1.10. The Novel Contribution to Science

The novel contribution to science constitutes:

- Developing a novel management tool for a commercial scallop species in the Isle of Man, that focussed on multiple objectives (environmental and economic).

- Developing an IBM in a relatively simple, effectively closed system, which has complete data coverage of fishing activity allowing comprehensive model validation at a relatively fine scale.

- Demonstrating the use of a choice based questionnaire survey technique (conjoint analysis) to understand more about what influences fishers' patch choice behaviour, and characterising fishers into different 'strategies' using this data (Shepperson et al., 2016).

- Developing an IBM that allowed us to test out multiple different behavioural structures to determine the most realistic behavioural rules to use when predicting the spatial displacement of effort following management.

- The first application of Approximate Bayesian Computation to validate a fisheries IBM.

- Providing a comparison of two types of vessel tracking data, vessel monitoring system and automatic identification system data, to highlight the advantages and drawbacks of each type (Shepperson et al., in submission).

1.11. References

Abernethy, K. E., Allison, E. H., Molloy, P. P., and Côté, I. M. 2007. Why do fishers fish where they fish ? Using the ideal free distribution to understand the behaviour of artisanal reef fishers. Canadian Journal of Fisheries and Aquatic Sciences, 64: 1595–1604.

Bacalso, R. T. M., Juario, J. V., and Armada, N. B. 2013. Fishers' choice of alternative management scenarios: A case study in the Danajon Bank, Central Philippines. Ocean & Coastal Management, 84: 40–53.

Bastardie, F., Nielsen, J. R., Andersen, B. S., and Eigaard, O. R. 2010a. Effects of fishing effort allocation scenarios on energy efficiency and profitability: An individual-based model applied to Danish fisheries. Fisheries Research, 106: 501–516.

Bastardie, F., Nielsen, J. R., and Miethe, T. 2014. DISPLACE: a dynamic, individual-based model for spatial fishing planning and effort displacement — integrating underlying fish population models. Canadian Journal of Fisheries and Aquatic Sciences, 71: 1–21.

Bastardie, F., Nielsen, J. R., Ulrich, C., Egekvist, J., and Degel, H. 2010b. Detailed mapping of fishing effort and landings by coupling fishing logbooks with satellite-recorded vessel geo-location. Fisheries Research, 106: 41–53.

Beddington, J. R., Agnew, D. J., and Clark, C. W. 2007. Current Problems in the Management of Marine Fisheries. Science, 316: 1713–1716.

Begossi, A. 1992. The use of optimal foraging theory in the understanding of fishing strategies: A case from Sepetiba Bay (Rio de Janeiro State, Brazil). Human Ecology, 20: 463–475.

Begossi, A., Clauzet, M., Hanazaki, N., Lopes, P. F., and Ramires, M. 2009. Fishers' decision making, optimal foraging and management. *In* III Seminario de Gestao Socioambiental para o Desenvolvimento Sustentavel da Aquicultura e da Pesca no Brasil - III SEGAP 2009, pp. 1–5.

Béné, C. 1996. Effects of market constraints, the renumeration system, and resource dynamics on the spatial distribution of fishing effort. Canadian Journal of Fisheries and Aquatic Sciences, 53: 563–571.

Bene, C., and Tewfik, A. 2001. Fishing Effort Allocation and Fishermen's Decision Making Process in a Multi-Species Small-Scale Fishery: Analysis of the Conch and Lobster Fishery in Turks and Caicos Islands. Human Ecology, 29: 157–186.

Branch, T. A., Hilborn, R., Haynie, A. C., Fay, G., Flynn, L., Griffiths, J., Marshall, K. N., *et al.* 2006. Fleet

dynamics and fishermen behavior: lessons for fisheries managers. Canadian Journal of Fisheries and Aquatic Sciences, 63: 1647–1668.

Bucaram, S. J., and Hearn, A. 2014. Factors that influence the entry–exit decision and intensity of participation of fishing fleet for the Galapagos lobster fishery. Marine Policy, 43: 80–88. Elsevier.

Bucaram, S. J., White, J. W., Sanchirico, J. N., and Wilen, J. E. 2013. Behavior of the Galapagos fishing fleet and its consequences for the design of spatial management alternatives for the red spiny lobster fishery. Ocean & Coastal Management, 78: 88–100.

Burgess, M., Drexler, M., Axtell, R., Bailey, R., Watson, J., Ananthanaryanan, A., Cabral, R., *et al.* 2017. The role of agent-based modeling in systems-based fishery management. Fish and Fisheries (In Review).

Cabral, R. B., Geronimo, R. C., Lim, M. T., and Aliño, P. M. 2010. Effect of variable fishing strategy on fisheries under changing effort and pressure: An agent-based model application. Ecological Modelling, 221: 362–369.

Cabrera, J. L., and Defeo, O. 2001. Daily bioeconomic analysis in a multispecific artisanal fishery in Yucatan, Mexico. Aquatic Living Resources, 14: 19–28.

Cambiè, G., Pantin, J. R., Lincoln, H., Hiddink, J. G., Lambert, G., and Kaiser, M. J. 2017. Diversity of fishing métier use can affect incomes and costs in small-scale fisheries. Canadian Journal of Fisheries and Aquatic Sciences.

Cartwright, S. J., Bowgen, K. M., Collop, C., Hyder, K., Nabe-Nielsen, J., Stafford, R., Stillman, R. A., *et al.* 2016. Communicating complex ecological models to non-scientist end users. Ecological Modelling, 338: 51–59.

Charles, A. T. 1995. Fishery Science - the Study of Fishery Systems. Aquatic Living Resources, 8: 233–239.

Charnov, E. L. 1976. Optimal Foraging, the Marginal Value Theorem. Theoretical Population Ecology, 9: 129–136.

Christensen, A.-S., and Raakjær, J. 2006. Fishermen's tactical and strategic decisions. A case study of Danish demersal fisheries. Fisheries Research, 81: 258–267.

Daw, T. M. 2008. Spatial distribution of effort by artisanal fishers: Exploring economic factors affecting the lobster fisheries of the Corn Islands, Nicaragua. Fisheries Research, 90: 17–25.

DeAngelis, D. L., and Mooij, W. M. 2005. Individual-based modelling of ecological and evolutionary processes. Annual Review of Ecology, Evolution, and Systematics, 36: 147 - 168.

de Oliveira, L. E. C., and Begossi, A. 2011. Last Trip Return Rate Influence Patch Choice Decisions of Small-Scale Shrimp Trawlers: Optimal Foraging in São Francisco, Coastal Brazil. Human Ecology, 39: 323–332.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES Journal of Marine Science, 60: 371–380.

Dowling, N. a, Wilcox, C., Mangel, M., and Pascoe, S. 2012. Assessing opportunity and relocation costs of marine protected areas using a behavioural model of longline fleet dynamics. Fish and Fisheries, 13: 139–157.

Durell, S. E. a. L. V. D., Stillman, R. a., Caldow, R. W. G., McGrorty, S., West, A. D., and Humphreys, J. 2006. Modelling the effect of environmental change on shorebirds: A case study on Poole Harbour, UK. Biological Conservation, 131: 459–473.

EC. 2009. Council Regulation (EC) No. 1224/ 2009 of 20 November 2009. Establishing a Community control system for ensuring compliance with the rules of the Common Fisheries Policy. Official Journal of the European Union, L343/1: 1–50.

Eggert, H., and Martinsson, P. 2004. Are commercial fishers risk-lovers? Land Economics, 80: 550–560.

Eigaard, O. R., Bastardie, F., Breen, M., Dinesen, G. E., Hintzen, N. T., Laffargue, P., Mortensen, L. O., *et al.* 2015. Estimating seabed pressure from demersal trawls, seines, and dredges based on gear design and dimensions. ICES Journal of Marine Science, 73: 24–43.

Evans, M. R., Grimm, V., Johst, K., Knuuttila, T., de Langhe, R., Lessells, C. M., Merz, M., *et al.* 2013. Do simple models lead to generality in ecology? Trends in ecology & evolution, 28: 578–83.

FAO. 2016. The State of World Fisheries and Aquaculture 2016. Food and Agriculture Organisation. 200 pp.

Fretwell, S. D., and Lucas, H. L. 1969. On territorial behaviour and other factors influencing habitat distribution in birds. Acta Biotheoretica, 19: 16–36.

Fulton, E. a, Smith, A. D. M., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Gatewood, J. B. 1983. Deciding where to fish: The skipper's dilemma in Southeast Alaskan salmon seining. Coastal Zone Management Journal, 10: 347–367.

Gelcich, S., Edwards-jones, G., and Kaiser, M. J. 2005. Importance of Attitudinal Differences among Artisanal Fishers toward Co-Management and Conservation of Marine Resources, 19: 865–875.

Gelcich, S., Godoy, N., and Castilla, J. C. 2009. Artisanal fishers' perceptions regarding coastal co-management policies in Chile and their potentials to scale-up marine biodiversity conservation. Ocean & Coastal Management, 52: 424–432.

Gillis, D. 2001. Influence of environment and fleet dynamics on catch rates of eastern Scotian Shelf cod through the early 1980s. ICES Journal of Marine Science, 58: 61–69.

Gillis, D. M. 2003. Ideal free distributions in fleet dynamics: a behavioral perspective on vessel movement in fisheries analysis. Canadian Journal of Zoology, 81: 177–187.

Girardin, R., Hamon, K. G., Pinnegar, J., Poos, J. J., Thébaud, O., Tidd, A., Vermard, Y., *et al.* 2016. Thirty years of fleet dynamics modelling using discrete-choice models: What have we learned? Fish and Fisheries. http://dx.doi.org/10.1111/faf.12194.

Goñi, R., Adlerstein, S., Alvarez-Berastegui, D., Forcada, A., Reñones, O., Criquet, G., Polti, S., *et al.* 2008. Spillover from six western Mediterranean marine protected areas: evidence from artisanal fisheries. Marine Ecology Progress Series, 366: 159–174.

Gordon, H. S. 1953. An economic approach to the optimum utilization of fishery resources. Journal of the Fisheries Research Board of Canada, 10: 442–457.

Goss-custard, J. D., Road, C., and Stillman, R. A. 2008. Individual-based models and the management of shorebird populations. Natural Resource Modeling, 21: 3–71.

Greiner, R., Patterson, L., and Miller, O. 2009. Motivations, risk perceptions and adoption of conservation practices by farmers. Agricultural Systems, 99: 86–104.

Griffen, B. D. 2009. Consumers that are not 'ideal' or 'free' can still approach the ideal free distribution using simple patch-leaving rules. The Journal of Animal Ecology, 78: 919–927.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., *et al.* 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 198: 115–126.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., and Railsback, S. F. 2010. The ODD protocol: A review and first update. Ecological Modelling, 221: 2760–2768.

Grimm, V., Frank, K., Jeltsch, F., Brandl, R., Uchmański, J., and Wissel, C. 1996. Pattern-oriented modelling in population ecology. Science of The Total Environment, 183: 151–166.

Grimm, V., and Railsback, S. F. 2005. Individual-Based Modeling and Ecology. Princeton University Press, Princeton.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H. H., *et al.* 2005. Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. Science, 310: 987-991.

Hallwass, G., Lopes, P. F. M., Juras, A., and Silvano, R. 2013. Behavioral and environmental influences on fishing rewards and the outcomes of alternative management scenarios for large tropical rivers. Journal of Environmental Management, 128: 274–82.

Hart, P. J. B. 2003. How can we create new management paradigms to resolve conflicts of interest in fisheries? American Fisheries Society Symposium, 38: 717–725.

Hilborn, R. 1985. Fleet Dynamics and Individual Variation: Why Some People Catch More Fish than Others. Canadian Journal of Fisheries and Aquatic Sciences, 42: 2–13.

Hilborn, R. 2007a. Moving to Sustainability by Learning from Successful Fisheries. AMBIO: A Journal of the Human Environment, 36: 296–303.

Hilborn, R. 2007b. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Hilborn, R., Fulton, E. A., Green, B. S., Hartmann, K., Tracey, S. R., and Watson, R. A. 2015. When is a fishery sustainable ? Canadian Journal of Fisheries and Aquatic Sciences, 1441: 1–46.

Hilborn, R., and Ovando, D. 2014. Reflections on the success of traditional fisheries management. ICES Journal of Marine Science, 71: 1040–1046.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., *et al.* 2004. When can marine reserves improve fisheries management? Ocean & Coastal Management, 47: 197–205.

Hintzen, N. T., Bastardie, F., Beare, D., Piet, G. J., Ulrich, C., Deporte, N., Egekvist, J., *et al.* 2012. VMStools: Open-source software for the processing, analysis and visualisation of fisheries logbook and VMS data. Fisheries Research, 115–116: 31–43.

Hinz, H., Murray, L. G., Lambert, G. I., Hiddink, J. G., and Kaiser, M. J. 2013. Confidentiality over fishing effort data threatens science and management progress. Fish and Fisheries, 14: 110–

117.

Holland, D. 2008. Are Fishermen Rational? A Fishing Expedition. Marine Resource Economics, 23: 325–344.

Hutton, T., Mardle, S., Pascoe, S., and Clark, R. 2004. Modelling fishing location choice within mixed fisheries: English North Sea beam trawlers in 2000 and 2001. ICES Journal of Marine Science, 61: 1443–1452.

Jager, W., Janssen, M. A., De Vries, H. J. M., De Greef, J., and Vlek, C. A. J. 2000. Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model. Ecological Economics, 35: 357–379.

Jennings, S., Smith, A. D. M., Fulton, E. A., and Smith, D. C. 2014. The ecosystem approach to fisheries: management at the dynamic interface between biodiversity conservation and sustainable use. Annals of the New York Academy of Sciences, 1322: 48–60.

Kahneman, D., and Tversky, A. 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47: 263–292.

Kaiser, M., Clarke, K., Hinz, H., Austen, M., Somerfield, P., and Karakassis, I. 2006. Global analysis of response and recovery of benthic biota to fishing. Marine Ecology Progress Series, 311: 1–14.

Kaiser, M. J., Hilborn, R., Jennings, S., Amaroso, R., Andersen, M., Balliet, K., Barratt, E., *et al.* 2016. Prioritization of knowledge-needs to achieve best practices for bottom trawling in relation to seabed habitats. Fish and Fisheries, 17: 637–663.

Kellner, J. B., Tetreault, I., Gaines, S. D., and Nisbet, R. M. 2007. Fishing the line near marine reserves in single and multispecies fisheries. Ecological Applications, 17: 1039–1054.

Lambert, G. I., Jennings, S., Hiddink, J. G., Hintzen, N. T., Hinz, H., Kaiser, M. J., and Murray, L. G. 2012. Implications of using alternative methods of vessel monitoring system (VMS) data analysis to describe fishing activities and impacts. ICES Journal of Marine Science, 69: 682–693.

Lee, J., South, a. B., and Jennings, S. 2010. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES Journal of Marine Science, 67: 1260–1271.

Lee, A. Van Der, Gillis, D. M., and Comeau, P. 2014. Comparative analysis of the spatial distribution of fishing effort contrasting ecological isodars and discrete choice models. Canadian Journal of Fisheries and Aquatic Sciences, 71: 141–150.

Leite, M. C. F., and Gasalla, M. A. 2013. A method for assessing fishers' ecological knowledge as a practical tool for ecosystem-based fisheries management: Seeking consensus in Southeastern Brazil. Fisheries Research, 145: 43–53.

Little, L., Kuikka, S., Punt, A., Pantus, F., Davies, C., and Mapstone, B. 2004. Information flow among fishing vessels modelled using a Bayesian network. Environmental Modelling & Software, 19: 27–34.

Little, L. R., Punt, A. E., Mapstone, B. D., Begg, G. a., Goldman, B., and Williams, A. J. 2009. An agent-based model for simulating trading of multi-species fisheries quota. Ecological Modelling, 220: 3404–3412.

MacArthur, R. H., and Pianka, E. R. 1966. On Optimal Use of a Patchy Environment. The American Naturalist, 100: 603–609.

Mackinson, S., Wilson, D. C., Galiay, P., and Deas, B. 2011. Engaging stakeholders in fisheries and marine research. Marine Policy, 35: 18–24.

Marchal, P., Andersen, B., Caillart, B., Eigaard, G. O., Hovgaard, H., Iriondo, A., Le Fur, F., *et al.* 2007. Impact of technological creep on fishing effort and fishing mortality, for a selection of European fleets. ICES Journal of Marine Science, 64: 192–209.

Marine Management Organisation. 2015. UK Sea Fisheries Statistics 2015. 174 pp. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/555665/UK_Sea_Fisheries_Statistics_2015_full_report.pdf.

Mccauley, B. D. J., Woods, P., Sullivan, B., Bergman, B., Jablonicky, C., Roan, A., Hirshfi, M., *et al.* 2016. Ending hide and seek at sea. Science, 351: 1148–1150.

McDonald, A. D., Little, L. R., Gray, R., Fulton, E., Sainsbury, K. J., and Lyne, V. D. 2008. An agent-based modelling approach to evaluation of multiple-use management strategies for coastal marine ecosystems. Mathematics and Computers in Simulation, 78: 401–411.

McKie, R. 2014. Bottom trawling: how to empty the seas in just 150 years. The Guardian. https://www.theguardian.com/environment/2014/feb/10/bottom-trawling-how-to-empty-the-seas.

Monbiot, G. 2015. Allowing scallop dredging in 'strictly protected' dolphin reserves is madness. The Guardian. https://www.theguardian.com/environment/georgemonbiot/2015/nov/09/allowing-scallop-dredging-in-strictly-protected-dolphin-reserves-is-madness.

Moustakas, A., Silvert, W., and Dimitromanolakis, A. 2006. A spatially explicit learning model of migratory fish and fishers for evaluating closed areas. Ecological Modelling, 192: 245–258.

Murray, L. G., Hinz, H., Hold, N., and Kaiser, M. J. 2013. The effectiveness of using CPUE data derived from Vessel Monitoring Systems and fisheries logbooks to estimate scallop biomass. ICES Journal of Marine Science, 70: 1330–1340.

Murray, L., Hinz, H., and Kaiser, M. 2011. Functional response of fishers in the Isle of Man scallop fishery. Marine Ecology Progress Series, 430: 157–169.

Myers, R. A., Fuller, S. D., and Kehler, D. G. 2000. A fisheries management strategy robust to ignorance: rotational harvest in the presence of indirect fishing mortality. Canadian Journal of Fisheries and Aquatic Sciences, 57: 2357–2362.

Myers, R. A., and Worm, B. 2003. Rapid worldwide depletion of predatory fish communities. Nature, 423: 280–283.

Natale, F., Gibin, M., Alessandrini, A., Vespe, M., and Paulrud, A. 2015. Mapping fishing effort through AIS data. PLoS ONE, 10: 1–16.

Nilsson, P., and Ziegler, F. 2007. Spatial distribution of fishing effort in relation to seafloor habitats in the Kattegat, a GIS analysis. Aquatic Conservation: Marine and Freshwater Ecosystems, 17: 421–440.

O'Donnell, K. P., Molloy, P. P., and Vincent, A. C. 2012. Comparing Fisher Interviews, Logbooks, and Catch Landings Estimates of Extraction Rates in a Small-Scale Fishery. Coastal Management, 40: 594–611.

Orians, G. H., and Pearson, E. 1979. On the Theory of Central Place Foraging. *In* Analysis of Ecological Systems. Ed. by D. J. Honrs, G. R. Stairs, and R. D. Mitchell. Ohio State University, Columbus.

Pascoe, S., and Mardle, S. 2005. Anticipating fisher response to management: Can economics help? ICES Annual Science Conference. Aberdeen.

Pauly, D., Christensen, V., Dalsgaard, J., Froese, R., and Torres, F. 1998. Fishing Down Marine Food Webs. Science, 279: 860–863.

Peterson, A. M., and Stead, S. M. 2011. Rule breaking and livelihood options in marine protected areas. Environmental Conservation, 38: 342–352.

Piet, G. J., Quirijns, F. J., Robinson, L., and Greenstreet, S. P. R. 2007. Potential pressure indicators for fishing, and their data requirements. ICES Journal of Marine Science, 64: 110–121.

Pikitch, E. K., Santora, C., Babcock, E. A., Bakun, A., Bonfil, R., Conover, D. O., Dayton, P., *et al.* 2004. Ecosystem-Based Fishery Management. Science, 305: 346-347.

Pita, C., Pierce, G. J., and Theodossiou, I. 2010. Stakeholders' participation in the fisheries management decision-making process: Fishers' perceptions of participation. Marine Policy, 34: 1093–1102.

Plagányi, É. E., Punt, A. E., Hillary, R., Morello, E. B., Thébaud, O., Hutton, T., Pillans, R. D., *et al.* 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries, 15: 1–22.

Poos, J. J., Bogaards, J. A., Quirijns, F. J., Gillis, D. M., and Rijnsdorp, A. D. 2010. Individual quotas, fishing effort allocation, and over-quota discarding in mixed fisheries. ICES Journal of Marine Science, 67: 323–333.

Ralston, S., Punt, A. E., Hamel, O. S., DeVore, J. D., and Conser, R. J. 2011. A meta-analytic approach to quantifying scientific uncertainty in stock assessments. Fishery Bulletin, 109: 217–231.

Rees, S. E., Rodwell, L. D., Searle, S., and Bell, A. 2013. Identifying the issues and options for managing the social impacts of Marine Protected Areas on a small fishing community. Fisheries Research, 146: 51–58.

Reeves, S., Marchal, P., Mardle, S., Pascoe, S., Prellezo, R., Thebaud, O., and Travers, M. 2009. From Fish to Fisheries: The Changing Focus of Management Advice. *In* Advances in Fisheries Science: 50 years on from Beverton and Holt. Ed. by A. Payne, J. Cotter, and T. Potter. Blackwell Publishing Ltd, Oxford, UK.

Renton, A. 2013. War on the seabed: the shellfishing battle. The Guardian. https://www.theguardian.com/environment/2013/feb/10/scallop-wars-on-britains-west-coast.

Rijnsdorp, A. D., Poos, J. J., Quirijns, F. J., HilleRisLambers, R., De Wilde, J. W., and Den Heijer, W. M. 2008. The arms race between fishers. Journal of Sea Research, 60: 126–138.

Röckmann, C., Ulrich, C., Dreyer, M., Bell, E., Borodzicz, E., Haapasaari, P., Hauge, K. H., *et al.* 2012. The added value of participatory modelling in fisheries management – what has been learnt? Marine Policy, 36: 1072–1085.

Russo, T., D'Andrea, L., Parisi, A., Martinelli, M., Belardinelli, A., Boccoli, F., Cignini, I., *et al.* 2016. Assessing the fishing footprint using data integrated from different tracking devices: Issues and opportunities. Ecological Indicators, 69: 818–827.

Salas, S., and Gaertner, D. 2004. The behavioural dynamics of fishers: management implications. Fish and Fisheries, 5: 153–167.

Sheikh, A. D., Rehman, T., and Yates, C. M. 2003. Logit models for identifying the factors that influence the uptake of new 'no-tillage' technologies by farmers in the rice–wheat and the cotton–wheat farming systems of Pakistan's Punjab. Agricultural Systems, 75: 79–95.

Shepperson, J., Murray, L. G., Cook, S., Whiteley, H., and Kaiser, M. J. 2014. Methodological considerations when using local knowledge to infer spatial patterns of resource exploitation in an Irish Sea fishery. Biological Conservation, 180: 214–223.

Simon, H. . 1955. A Behavioural Model of Rational Choice. The Quarterly Journal of Economics, 69: 99–118.

Smith, M. D., Lynham, J., Sanchirico, J. N., and Wilson, J. A. 2010. Political economy of marine reserves: Understanding the role of opportunity costs. Proceedings of the National Academy of Sciences, 107: 18300–18305.

Sosis, R. 2002. Patch Choice Decisions among Ifaluk Fishers. American Anthropologist, 104: 583–598.

Stillman, R. a. 2008. MORPH—An individual-based model to predict the effect of environmental change on foraging animal populations. Ecological Modelling, 216: 265–276.

Stillman, R. a, and Goss-Custard, J. D. 2010. Individual-based ecology of coastal birds. Biological reviews of the Cambridge Philosophical Society, 85: 413–34.

Teixeira, J. B., Martins, A. S., Pinheiro, H. T., Secchin, N. A., Leão de Moura, R., and Bastos, A. C. 2013. Traditional Ecological Knowledge and the mapping of benthic marine habitats. Journal of environmental management, 115: 241–50.

Toft, J. E., Punt, A. E., and Little, R. 2011. Modelling the economic and ecological impacts of the transition to individual transferable quotas in the multispecies US west coast groundfish trawl fleet. ICES Journal of Marine Science, 68: 1566–1579.

Toral, G. M., Stillman, R. a., Santoro, S., and Figuerola, J. 2012. The importance of rice fields for glossy ibis (Plegadis falcinellus): Management recommendations derived from an individual-based model. Biological Conservation, 148: 19–27.

Tversky, A., and Kahneman, D. 1974. Judgement under Uncertainty: Heuristics and Biases. Science, 185: 1124–1131.

van der Vaart, E., Beaumont, M. A., Johnston, A. S. A., and Sibly, R. M. 2015. Calibration and

evaluation of individual-based models using Approximate Bayesian Computation. Ecological Modelling, 312: 182–190.

van der Vaart, E., Johnston, A. S. A., and Sibly, R. M. 2016. Predicting how many animals will be where: How to build, calibrate and evaluate individual-based models. Ecological Modelling, 326: 113–123.

van Putten, I. E., Kulmala, S., Thébaud, O., Dowling, N., Hamon, K. G., Hutton, T., and Pascoe, S. 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish and Fisheries, 13: 216–235.

Vanslembrouck, I., Huylenbroeck, G., and Verbeke, W. 2002. Determinants of the Willingness of Belgian Farmers to Participate in Agri-environmental Measures. Journal of Agricultural Economics, 53: 489–511.

Voges, E., Gordoa, A. N. A., and Field, J. G. 2005. Dynamics of the Namibian hake fleet and management connotations: application of the ideal free distribution. Scientia Marina, 69: 285–293.

Voinov, A., and Bousquet, F. 2010. Modelling with stakeholders. Environmental Modelling & Software, 25: 1268–1281.

West, A. D., Yates, M. G., McGrorty, S., and Stillman, R. a. 2007. Predicting site quality for shorebird communities: A case study on the Wash embayment, UK. Ecological Modelling, 202: 527–539.

Wilen, J. E. 1979. Fishernan Behavior and the Design of Efficient Fisheries Regulation Programs. J. Fish. Res. Board Can., 36: 855–858.

Wilen, J. E. 2006. Why Fisheries Management Fails: Treating Symptoms Rather than the Cause. Bulletin of Marine Science, 78: 529–546.

Wilen, J. E., Smith, M. D., Lockwood, D., and Botsford, L. W. 2002. Avoiding Surprises: Incorporating Fishermen Behaviour into Management Models. Bulletin of Marine Science, 70: 553–575.

Worm, B., Barbier, E. B., Beaumont, N., Duffy, J. E., Folke, C., Halpern, B. S., Jackson, J. B. C., *et al.* 2006. Impacts of Biodiversity Loss on Ocean Ecosystem Services. Science, 314: 787–790.

Worm, B., Hilborn, R., Baum, J. K., Branch, T. A., Collie, J. S., Costello, C., Fogarty, M. J., *et al.* 2009. Rebuilding Global Fisheries. Science, 325: 578–585.

Yates, K. L. 2014. View from the wheelhouse: Perceptions on marine management from the fishing community and suggestions for improvement. Marine Policy, 48: 39–50.

CHAPTER 2: Use of a Choice-Based Survey Approach to Characterise Fishing Behaviour in a Scallop Fishery

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2.1. Abstract

The predictability of fisher behaviour is an area of considerable uncertainty in fisheries management models. Fisher-derived data could underpin a better understanding, and more realistic predictions, of fishing behaviour.

Face to face interviews and a choice-based survey were conducted with scallop fishers to collect foraging parameters that could inform a model of fishing activity, and to better understand patch choice behaviour. Importantly, survey data were validated against vessel monitoring system and logbook data where possible, demonstrating a good level of accuracy. Environmental parameters central to patch choice were determined (e.g. wave height, distance to port), and three strategies of patch choice behaviour were identified, termed quantity maximiser, quality maximiser, and efficient fisher. Individuals' VMS and logbook data further confirmed and explained these behavioural patterns.

This approach provided reliable, highly relevant data for the parameterisation of a fisheries behavioural model, which could lead to more robust and realistic predictive fisheries models.

2.2. Introduction

2.2.1. We need trusted predictive models for effective fisheries management

Hunter-gatherers, such as fishers, typically lack trust in the scientific evidence that underpins management controls and policy. This phenomenon is termed the 'credibility crisis' (Röckmann et al., 2012). Fishers often express the opinion that data collected by scientists do not sufficiently reflect the status of their fishery, leading to inappropriate management conclusions (Bergmann et al., 2004). The integration of public participation in science has been demonstrated to address some of the concerns surrounding credibility and uncertainty in fisheries (Voinov and Bousquet, 2010; Yates, 2014). In particular, participatory modelling can alleviate some of the tensions between scientists and fishers, through addressing questions surrounding the credibility and legitimacy of scientific advice based on 'black box' models (Röckmann et al., 2012; Thébaud et al., 2014). Quantitative and qualitative scientific models are the primary tool for generating advice for the purpose of natural resource management (Röckmann et al., 2012). Accordingly, there is a need to adopt approaches that assist in the development of more realistic, credible and trusted predictive management models, capable of predicting both ecological and economic impacts of novel future scenarios (Fulton et al., 2011; Reeves et al., 2009; Wilen et al., 2002).

2.2.2. Predictive models require a better understanding of fishing behaviour

Whilst the long term sustainability objectives of fishers and scientists are aligned (Kraak et al., 2010), in the short term fishers may be working to different priorities that operate under different spatial and time scales (Röckmann et al., 2012). Management measures that lead to short term reductions in fishing effort typically result in short term economic losses for some fishers. It is necessary to understand fishers' tolerance and capacity to cope with change to be able to understand which measures would engender support compared to those that are unacceptable. We need to understand how fishers will respond to management in terms of the spatial and temporal displacement of effort. If we can understand and predict the scope for fishers' compensatory activity following management restrictions, we can calculate realistic economic impacts of management, and reach more agreeable management solutions.

Nevertheless, the predictability of fishing behaviour is an area of considerable uncertainty in fisheries management (Fulton et al., 2011). Human decision-making drives spatial patterns of fishing

effort (Hilborn, 2007; Plagányi et al., 2014). We must understand what underlies these fishing

decisions, regarding where and when to fish, if we are to understand how fishing behaviour

underpins the spatial and temporal patterns in fishing activity that arise from external factors.

Hilborn (2007) stated that "managing fisheries is managing people" and so effective management

requires an "understanding of the motivation of fishermen and designing a management regime that

aligns societal objectives with the incentives provided to fishermen". This notion has been expressed

and reiterated by many fishery scientists over the decades (Bucaram et al., 2013; Hallwass et al.,

2013; Wilen, 2006, 1979), yet a generation of 'command and control' fishing policies, where top

down legislative measures prescribe where and when fishermen can fish, has somewhat failed to

take account of the societal and economic dimensions of fisheries (Bucaram and Hearn, 2014;

Bucaram et al., 2013; Wilen, 2006). Environmental policies are generally developed centrally, based

on the assumption that resource users will respond homogenously to management actions (Gelcich

et al., 2005). Whilst fishers' responses to management options may be deterministic, responses are

likely to vary between groups and among individuals which necessitates a thorough understanding

of the system to make realistic predictions about the effectiveness of management (Gelcich et al.,

2005).

2.2.3. Individual-based models could work from a behavioural perspective, but are data intensive

Individual-based models (IBMs) are considered better for predicting individual responses to novel

conditions compared to numerical modelling, as individuals can respond to experienced conditions

to maximise an objective function (such as fitness) (Grimm and Railsback, 2005; Railsback, 2001). In

a fishery, the objective function could be to maximise the economic return (equivalent to fitness),

but it could also be influenced by a range of social and environmental variables (Abernethy et al.,

2007). Despite the demonstrated utility of theoretical individual-based models (Cabral et al., 2010;

Ruiz-Pérez et al., 2011; Soulié and Thébaud, 2006), there are relatively few applications of IBMs to

real life fisheries (see Bastardie et al., 2014, 2010; Dowling et al., 2012), perhaps due to the limited

understanding of fisher behaviour. Vessel monitoring system (VMS) and logbook data (which when

linked provide spatially resolved catch records) are increasingly used to investigate fishing behaviour

(Lee et al., 2010; Murray et al., 2011). While VMS data can offer valuable insights into where and

when fishing occurs, it does not impart much insight into the decision making process that resulted

in the observed patterns of fishing effort. Fishers' data can provide insights into the decision making

at a finer scale than can be inferred from VMS data alone. For example, by collecting data directly

from fishers through surveys, it could be possible to identify the objective function of fishers, and thereby determine to what extent profit maximisation is actually driving fishing behaviour in relation to other drivers (Abernethy et al., 2007; Christensen and Raakjær, 2006). This information could inform the behavioural parameters used to develop an IBM of fishing behaviour and thereby predict more realistic and adaptive behavioural patterns in the fishery.

2.2.4. Participatory modelling can make models more transparent and realistic, increasing trust

It is increasingly acknowledged that better management decisions can be implemented when stakeholders are engaged in the decision making process, e.g. through participatory modelling (Gelcich et al., 2008; Mackinson 2011; Voinov and Bousquet, 2010). Stakeholders can be involved in; 1) framing the problem and purpose of the model, 2) using and evaluating the model (indirect participation), and 3) directly contributing to model construction (direct participation). Direct participation can increase support, interest and legitimacy (Mackinson and Wilson, 2014; Röckmann et al., 2012). The present study used questionnaires and a conjoint analysis technique to collect data directly from fishers to better understand fishing behaviour, in a first step towards a participatory modelling approach.

Conjoint analysis and related choice modelling methods are used in market research, to evaluate respondent preferences for a number of products with varying features (Green and Srinivasan, 1990). Conjoint analysis quantifies how an individual values a given product with a number of specific features or attributes, so determining which of the features of the product are preferred (Alriksson and Öberg, 2008). Rather than directly asking respondents what they prefer in a product or what influences their decision, a conjoint analysis simulates a more realistic choice context; i.e. respondents cannot simply state that all attributes are important, they are forced to rank them through making trade-offs between products (Orme, 2010). For example, a fisher is likely to state that the sea state, distance to port, and expected catch rate are all crucial in deciding where to fish. Nevertheless, this information would not be very meaningful when trying to understand the choices a fisherman makes when deciding where to fish (e.g. what is the trade-off between sea state [risk] and catch rate?). Whilst conjoint analysis has been used widely in marketing, healthcare, quality management and transportation studies, it has been used less often in an environmental context, although it is increasing in use (see Alriksson and Öberg, 2008 for review). In fisheries, conjoint analyses have been used to investigate the importance of fisheries management objectives (Wattage et al., 2005), and perceived impacts of regulatory obligations (Hadjimichael et al., 2013). We propose

that a conjoint analysis may also be a useful technique to elicit behavioural data from fishers that could be used to determine response thresholds within a model context.

2.2.5. Aims

The present study sought to determine whether it was possible to elicit realistic and reliable behavioural data from scallop fishers, using a questionnaire survey and conjoint analysis. The specific objectives were to i) further our understanding of fishing behaviours, focussing on the limiting factors and relationships between fishing behavioural parameters and fisher/vessel characteristics; ii) demonstrate the value of conjoint analysis for understanding patch choice behaviour; iii) characterise the behavioural characteristics of fishers, highlighting heterogeneity, and iv) provide evidence for the validity of such survey data.

2.3. Methods

2.3.1. Conjoint Analysis Design

A conjoint analysis was applied by conceptualising a fishing patch as a commercial product for respondents to choose between, with variable attributes (Table 2.1). Fishers were presented with a choice of fishing patches with different attribute levels and were asked to select the patch in which they would fish preferentially. Different levels of an attribute refer to the actual details of a product, e.g. if one of the patch attributes is sea state, the levels could be calm, moderate, or rough. The survey was designed to elicit a fisher's preferences for particular patch conditions, in terms of where they would rather fish using their current vessel. Understanding fishers' preferences would identify important attributes that influence fishers' decisions on where to fish, and the variation among individual fishers. An adaptive choice based conjoint (ACBC) survey was constructed and fielded in Sawtooth Software SSI Web v.8.2.4. The ACBC survey design was selected as the most appropriate as it is capable of handling small sample sizes, and a larger number of attributes and levels. In addition, the survey is adaptive, in that the software automatically and continually tailors the choices presented to the respondent according to their previous answers, resulting in a shorter interview with a greater level of respondent engagement (Sawtooth Software Inc., 2014).

Attributes and levels were chosen through informal discussion with relevant experts, including a researcher familiar with the conjoint analysis technique, scientists at the Centre for Environment, Fisheries, and Aquaculture Science (Cefas) and Bangor University, and a well-respected fisher within the scallop industry. A total of six attributes were used in this study, with a combined total of 26 levels between them. The levels for each attribute were selected such that they were relevant to inshore scallop fisheries (Table 2.1). Patches were attributed with an expected tow quality, i.e. how many scallops the fisher could expect to catch. However, it was necessary to standardise this catch rate so that it was relevant to different sized vessels. Vessels fish with different numbers of dredges depending on their size, therefore catch rates can be standardised as scallop weight per dredge, per tow hour. However, providing a catch rate of scallop weight per dredge hour in the conjoint analysis would require a respondent to repeatedly upscale this up to the catch rate relevant to their vessel to evaluate the patch, which would add substantially to the complexity of the survey. It was therefore decided to class expected tow quality as good, average or poor tows in the patch attributes, and to ask fishers to define what they consider as a good, average or poor tow prior to the survey.

Table 2.1. Attributes and their levels used to differentiate between fishing patches in the conjoint analysis.

Attribute	Levels	Explanation
Sea State	Calm, slight, moderate, rough, very rough, high	This refers to the sea conditions of a patch, derived from a combination of the wave height and wind speed.
Distance to Port	5, 10, 20, 30, 50, 80	The distance of a fishing patch from a vessel's port location, in nautical miles.
Tow Quality	Low, average, high	The catch per unit effort of a fishing patch, i.e. how many bags of scallops a fisher would expect to catch in a one hour tow.
Meat Quality	Low (12%), average (16%), high (20%)	The yield of the meat inside of the scallop.
Roe Status	Roe empty, roe full	The reproductive status of the scallop. Roe refers to the gonads of the scallop; a scallop with a full roe is more valuable than a scallop with empty roe.
Cobble	1%, 10%, 20%, 30%, 50%, 80%	This refers to the ground type, and how much stone the dredges pick up. A higher proportion of rocks in the dredges would result in longer sorting times, and potentially more damage to the gear and the catch.

In a conjoint analysis, each of the attribute levels has a particular value for the respondent, influencing how much they like the product; termed the utility. In this analysis, instead of products, there were fishing patches that were described by attributes such as sea state or distance to port. Within an attribute (e.g. sea state) there were different levels (e.g. rough, moderate, calm). Following the ACBC survey, the importance of each attribute, and the utility of each level was calculated using Sawtooth Software. The importance of an attribute relates to which attribute had the biggest influence on a respondent's patch choice, and the utility of each level relates to how much positive or negative influence that level has on the respondent's patch choice.

2.3.2. The Survey

The conjoint survey consisted of three different sections; demographic data collection, a screening section, and the choice task. Fishers were first presented with possible fishing patches in what is called the screening section; fishers simply indicated if it was possible or not possible that they would fish in each of the fishing patches, based on the varying attribute levels shown. This identified a set of possible fishing patches that fishers were later asked to choose between. During this

screening section, the software continually analysed respondent answers for non-compensatory screening rules, where a respondent systematically avoided an attribute level (e.g. high sea state). It then automatically asked the respondent if the level was completely unacceptable, and could remove it from subsequent questions. The software also screened for patch conditions that were an absolute requirement. For example, a respondent may only select patches that are less than 30 miles away. When presented with possible unacceptable or must-have options, a 'none of the above' option was included to reduce the chance of marking simply *undesirable* levels as completely unacceptable. This adaptive nature of the ACBC means that the questions gradually become more relevant to each individual, allowing a broader scope to the survey as a greater range of attributes can be tested initially. This approach is also more engaging for participants, which results in higher quality data (Sawtooth Software Inc., 2014).

In the choice task section patches that were highlighted as possible fishing patches during the previous screening section were then presented in groups of three. Respondents chose the fishing patch that they preferred the most out of the three presented. The preferred patch from each group of three was then presented in the next round, until through an iterative process of elimination, respondents finally eliminated all but their most preferred fishing patch. The aim of the survey was not specifically to reach this preferred patch concept, but to analyse the trade-off decisions made by the respondent (which become increasingly difficult) as the patches become more similar in their attributes.

2.3.3. Semi-structured Questionnaire Survey Design

A semi-structured questionnaire was conducted alongside the conjoint analysis, to elicit further behavioural parameters and vessel characteristics from the fishers. The questionnaire was also used to gain input on the model design in relation to management scenarios. The questionnaire consisted of five sections: (1) vessel characteristics such as ownership, size, catching power, and crew details; (2) limiting factors and extreme restrictions to fishing, such as weather conditions, maximum limiting distances, and limits to the time spent at sea; (3) behavioural parameters related to average fishing conditions, such as the normal time spent at sea; (4) economic requirements of the vessel, such as a minimum viable catch, and the costs of fishing; and (5) the ways in which management actions have affected fishing activity, and opinions in relation to management and the use of an IBM simulation tool.

2.3.4. Fielding the Survey

Individual fishers on the Isle of Man were contacted by email and then followed up with a phone call to explain more about the project and to arrange a time to meet face to face to complete the interview. The majority of interviews took place on fishing vessels or at the office of the producer organisation. The whole survey could be completed in 45 minutes, of which the conjoint analysis took from 7 to 25 minutes. Nevertheless, many fishers digressed additional useful contextual information, resulting in longer survey times. Whilst survey time could have been minimised, the additional discussion was viewed as important for building relationships of trust. This data collection was subject to Bangor University's ethics approval process.

2.3.5. Data Analysis

A conjoint utility indicates a fisher's preference for each level within each attribute. The conjoint utilities were calculated with a built-in Sawtooth software Hierarchical Bayes (HB) tool, to determine the utility score for each level of each attribute for each individual respondent (Sawtooth Software Inc., 2014). The HB tool is used to overcome the problem of sparse information, as each respondent only provides a small amount of information on a proportion of the hundreds of possible patch combinations within the survey. Instead of estimating each respondent's utilities individually, the HB algorithm estimates the difference between each respondent's individual data and average utilities for the entire sample. It then adjusts each individual's utilities, depending on the variability in the sample average; the more variance in the sample averages, the more the algorithm uses the individual's data (Sawtooth Software Inc., 2009). The importance of each attribute is then calculated from the scale of difference in utilities. For a simple example of how the importance is calculated, consider the following respondent's response to patch conditions:

Sea State	Utility	Distance from Port	Utility
Rough	0	10 miles away	60
Moderate	20	20 miles away	20
Calm	70	30 miles away	10
Range of utilities	70		50

The importance of each attribute (sea state and distance to port) as a percentage is calculated as:

Importance of attribute = range of utilities for that attribute / sum of ranges across all attributes

Therefore in this example:

Importance of sea state = (70-0) / (70+50) = 0.58

Importance of distance to port = (60-10) / (70+50) = 0.42

Sea state would be considered more important than distance from port for patch choice in this case. It is also possible to predict how fishers might choose between patches. This respondent should prefer a calm patch at a distance of 30 miles away from port (total utility 80) over a moderate patch at a distance of 20 miles away from port (total utility 40). The same respondent should be indifferent to a choice between a moderate patch 10 miles away, and a calm patch 30 miles away (both total utility of 80).

A principal components analysis (PCA) was used to identify the similarity among the different strategies adopted by each individual fisher in relation to patch choice. The strategy of an individual fisher was described by the importance scores for each patch attribute in the conjoint analysis. As there were six attributes, each fisher's strategy was described by their importance scores for each of the six attributes. The first three principal components accounted for 88% of the variance in the importance scores. The data were standardised and then a similarity matrix was calculated from the conjoint importance scores for all fishers, using Euclidean Distance. A cluster analysis was then used to identify whether fishers could be grouped by the similarity in their responses in the conjoint analysis, i.e. fishers who placed similar importance on each patch attribute.

Having identified different groupings of fishers based on the cluster analysis of the conjoint importance scores, the analysis then explored whether the similarities in strategy within each grouping of fishers were supported by each individual's corresponding questionnaire responses, and in the trips and catches recorded in those fishers' VMS and logbook data. A Kruskal-Wallis test, with Dunn's post hoc testing adjusted for ties, was used to compare the questionnaire survey responses among fishers, with the cluster set as the factor (Kruskal and Wallis, 1952). General or generalised linear models (GLMs, Nelder and Wedderburn, 1972) were used to explore differences in logbook variables recorded by vessels in each of the behavioural groupings, with the logbook variable as the response, and the cluster as the explanatory factor (see Table 2.4 for list of significant logbook variables). Akaike's Information Criterion (AIC) was used to select the best model fit between a Gaussian or Gamma family for each variable tested (Akaike, 1973).

Relating trip characteristics to the clusters provided context within which to understand more about each of the different behavioural strategies adopted by fishers. E.g. If fishers that placed the highest importance on roe status (i.e. valuable product) were also the fishers who had the highest value per unit fuel, it could be concluded that these fishers were successfully targeting a high quality product. This comparison of the conjoint analysis and questionnaire data with the individuals' VMS and logbook data allowed verification of the questionnaire responses, as well as the behavioural patterns identified in the conjoint analysis. It was possible to determine to what extent the behavioural strategies identified in the cluster analysis were reflected in the catch records of those fishers. In addition, the accuracy of the behavioural parameters provided during the questionnaire (e.g. minimum viable catch, distance travelled) was verified by comparing them to those derived from logbook data. The PCA and cluster analysis were performed in PRIMER (v.6) (Clarke and Gorley, 2006), all other statistical analyses were performed in R Version 3.1.2 (R Core Team, 2016).

2.4. Results

A total of 14 conjoint analysis responses were available for analysis. The sample size represented 56% of the 25 active IOM scallop vessels. Vessels ranged from 9.9m to 16m in length. Despite a slight skew towards larger vessels, the vessels surveyed were representative of the IOM fleet by length (Figure 2.1, Welch's $F_{(3, 29.85)}$ = 0.73, p= 0.17). The questionnaire is thus representative of the inshore IOM fishery, but may not be representative of the wider UK fleet as it fails to account for the larger vessels, despite displaying a borderline non-significant difference in lengths (Welch's $F_{(3, 32.216)}$ = 1.88, p = 0.07). The maximum number of dredges used by each vessel ranged from 4 to 8 per side. Respondents had a range of fishing experience, from 3 to 62 years fishing. Six fishers owned their own vessels, and had been vessel owners from 8 months to 31 years.
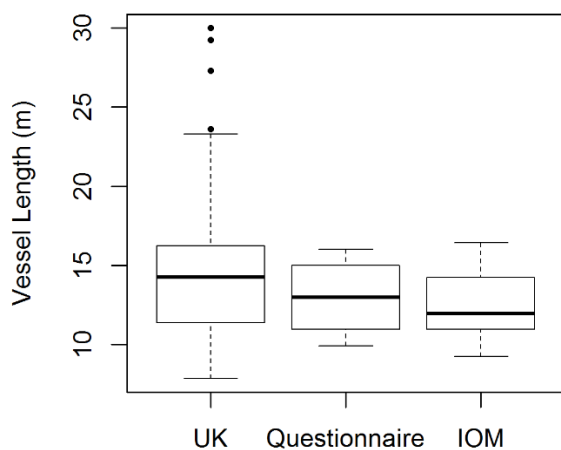
Figure 2.1 Lengths of vessels fishing in ICES square 36E5 and 37E5 between 2008 and 2014. "UK" refers to all UK scallop vessels recorded in the logbook data, "IOM" refers to all Isle of Man scallop vessels in the logbook data, and "Questionnaire" refers to the population of IOM scallop vessels included in the questionnaire survey.

2.4.1. Questionnaire responses provided foraging parameters relevant to parameterising a fisheries behavioural model

Questionnaire behavioural response values (i.e. questions concerning fishing activity) were compared with the demographic variables and vessel characteristics to identify heterogeneity in behavioural and energetics rules. Responses were compared with vessel length and vessel capacity units (VCU, VCU = (length * beam) + (engine power (kW) * 0.45), Pascoe and Gréboval, 2003), to construct size based rules that could account for the variability in ability and requirements of different sized vessels in a model. VCU had a stronger correlation with many variables than vessel length, suggesting that VCU may be a better metric when defining different behaviours for different

categories of vessels (Appendix 1). Average number of crew, maximum number of dredges used, fuel use, what might be considered as good takings, storage space, and fishing costs for a day of fishing were all significantly correlated with VCU with R^2 values all > 0.6 (Figure 2.2, Appendix 1). However, if the single point for a large vessel is removed the correlation coefficients fall to 0.79 for average crew, 0.80 for max dredges, 0.74 for fuel use, 0.58 for good takings, 0.53 for max bags stored, and the costs per day are no longer significantly correlated. Further data collection for larger vessels would provide more insight into these patterns.
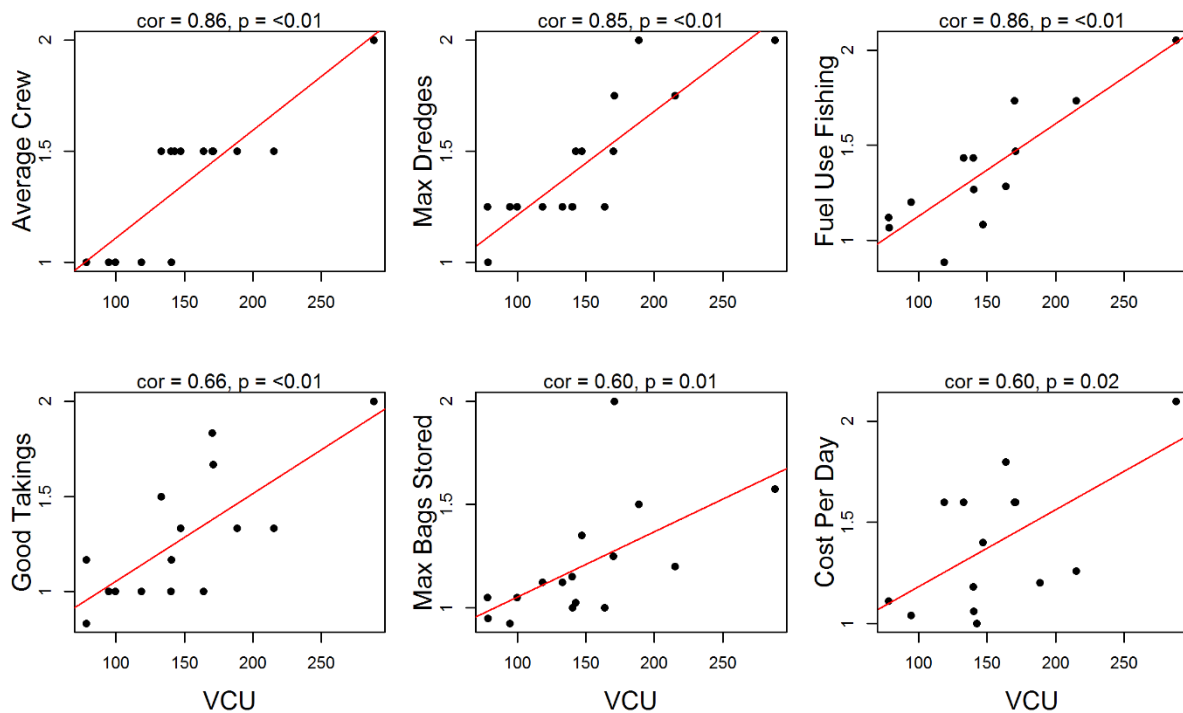
Figure 2.2: Pearson correlation between vessel characteristics collected from the questionnaire and the size of the vessel (VCU). Values on the y axis are presented as a scaled response for confidentiality.

2.4.2. Conjoint analysis increased our understanding of fishing decisions that drive patch choice behaviour

The conjoint analysis demonstrated that sea state was the most important attribute that influenced the choice of fishing patch (Table 2.2). This was followed by distance to port, and then tow quality. Meat quality, roe status and cobble were relatively similar, but of lower importance.

Table 2.2. Importance of each patch attribute, and the utility score of each attribute level in the conjoint analysis.

Attribute	Attribute Importance		Attribute Levels	Utility Score	
	Mean	Standard Deviation		Mean	Standard Deviation
Sea State	34.92	13.71	Calm	100.92	38.48
			Slight	92.47	40.83
			Moderate	75.66	37.50
			Rough	-54.40	25.92
			Very rough	-106.06	44.74
			High	-108.60	44.08
Distance to port	24.43	8.09	5mn	59.58	15.43
			10nm	38.09	13.51
			20nm	24.58	13.67
			30nm	4.81	13.03
			50nm	-34.03	24.57
			80nm	-93.03	42.35
Tow quality	17.00	6.82	Low	-59.79	25.16
			Average	17.56	13.73
			High	42.22	17.26
Cobble	8.14	2.36	1%	25.99	5.87
			10%	13.23	3.56
			20%	3.83	2.41
			30%	-5.38	2.47
			50%	-14.39	4.02
			80%	-22.83	8.93
Roe Status	7.44	6.14	Roe empty	22.32	18.42
			Roe full	-22.32	18.42
Meat quality	7.07	1.56	Low (12%)	-14.27	6.21
			Average (16%)	-13.86	3.09
			High (20%)	28.13	3.14

The software calculated utility scores for each level of each attribute for each individual, depending on how they responded to the patches presented to them, e.g. rough sea state has a negative utility score therefore it was having a negative influence on a fisher's likelihood of choosing a patch. Individual attribute level utility curves were derived from the results of the conjoint analysis (Figure 2.3). Relatively consistent thresholds can be seen at the point on the graph where each attribute changes from a positive to a negative utility (Figure 2.3). For example, sea state changed from a positive to negative utility score between moderate and rough for all vessels. The percentage of cobble also had a relatively consistent threshold of around 25% cobble in the catch. A poor tow quality had a negative utility, while both a poor and an average meat quality had a negative utility. The threshold was less clear for the distance to port, which indicated that there was more heterogeneity among fishers for this attribute. Some fishers showed a negative utility score at 30nm away from port, whereas other fishers were tolerant of a distance up to 50nm. The response to roe

status was also heterogeneous, such that some fishers had a steep change in utility between empty roe and full roe, while other fishers had very little difference between the utility of empty and full roe. The latter may be driven by the specific market for which the scallops are destined.
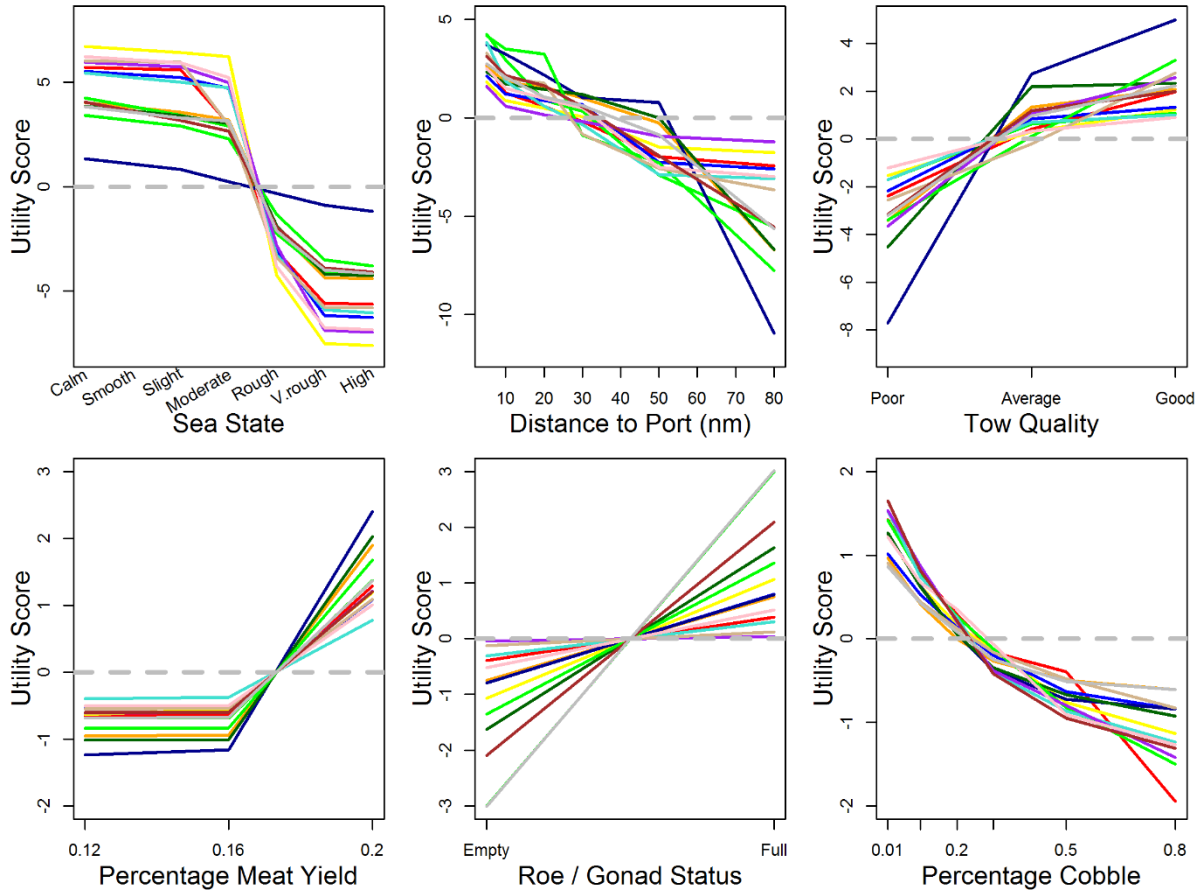
Figure 2.3. Individual fishers' utility scores for each attribute in the patch choice conjoint analysis, completed during interviews with fishers from the Isle of Man scallop fishery. Note that the y-axes differ among the graphs.

2.4.3. Heterogeneity in conjoint responses could be used to categorise fishers into different behavioural groups

The PCA on the individual importance scores revealed that there were clearly demarcated individual strategies in relation to how patch choice is made (Figure 2.4). The first three principal components (PCs) accounted for 88% of the variance in the importance scores. PC1 was related to a higher importance of sea state and cobble, and a lower importance of distance to port, tow quality, meat yield, and roe status. PC2 was related to a higher importance of distance to port and roe status, and a lower importance of sea state, tow quality and meat yield. PC3 related to a higher importance of sea state, tow quality, meat yield and roe status, but a lower importance of distance to port and

cobble. These multivariate patterns in importance scores provide insight into the different fishing strategies.
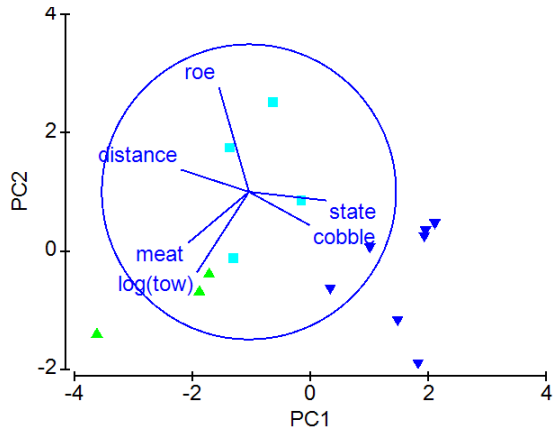
Figure 2.4 Principal component biplot showing the multivariate differences in each individual's perceived importance of each patch attribute in the conjoint analysis. Dark blue triangles relate to fisherss later classified as cluster 1, green triangles relate to fishers in cluster 2, and light blue squares relate to fishers in cluster 3.

The importance of sea state, cobble and distance to port distinguished cluster 1 (7 fishers) from the other two clusters, tow quality and meat yield distinguished cluster 2 (3 fishers), and roe status distinguished cluster 3 (4 fishers) from the other clusters (Figure 2.5). The three clusters of fishers could be considered as having three different strategies for patch choice, such that each strategy was characterised by the discriminating attributes.
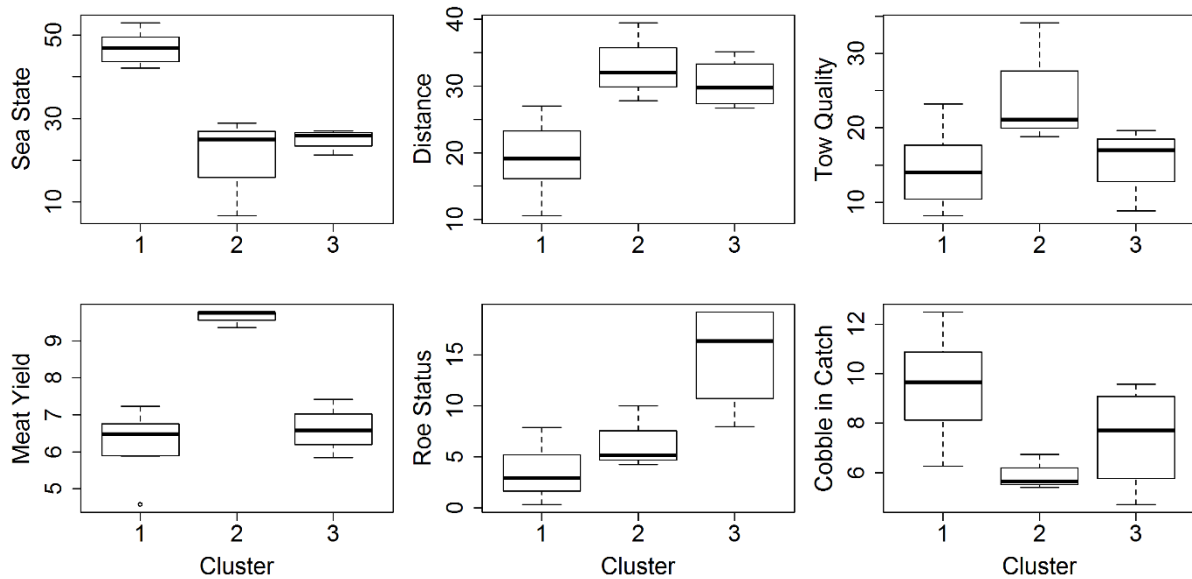
Figure 2.5. Importance scores for each patch attribute in the conjoint analysis, grouped according to each strategy identified in the cluster analysis. The boxplots display the minimum, 1st quartile, median, 3rd quartile, and maximum values.

2.4.4. Questionnaire responses were used to link vessel characteristics to the behavioural clusters, to understand the types of vessels that formed each group

Variables that showed a significant difference between the clusters are presented in Table 2.3. VCUs and vessel length differed significantly between clusters 2 and 3, with cluster 2 representing the largest vessels. There was no significant size difference between cluster 1 and 2, but all size based characteristics (VCU, length, tonnage) were lower in cluster 1, and VCU showed a trend towards significance (p=0.08). Size could therefore be considered as an indicator of different behavioural strategies. Fishers in cluster 2 were the largest vessels, travelled fastest, and used the most fuel. Fishers in cluster 1 were mid-sized vessels, although not significantly different to cluster 2. Fishers in cluster 3 were the smallest vessels, had the lowest VCU, and had the lowest economic requirements.

Table 2.3. Kruskal-Wallis results to determine significant differences in vessel characteristics and behaviours recorded in the questionnaire interview, between behavioural strategy clusters identified in the conjoint analysis. Dunn's post hoc testing reveals the differences between groups. Degrees of freedom vary where some fishers did not provide a response to a question. Dark green is statistically significant at p = 0.05, light green is significant at p=0.1.

Questionnaire Variable	DF	K-W Chi-sq	P	Median per cluster			Dunn's p value		
				1	2	3	2-1	3-1	2-3
VCU	2,11	6.44	0.04	147	215	129	0.08	0.247	0.011
Vessel length	2,11	6.51	0.04	14.6	15	10.9	0.159	0.123	0.011
Tonnage	2,7	6.79	0.03	27	40	14.8	0.083	0.311	0.01
Average Crew	2,11	6.23	0.04	3	3	2	0.287	0.075	0.015
Max Steaming[1]	2,11	6.05	0.048	8.5	9.5	8.1	0.018	0.863	0.045
Fuel per fishing hour	2,8	7.54	0.02	23	32	16	0.068	0.223	0.007
Min Viable Gross[2]	2,11	7.31	0.026	900	1000	500	0.139	0.086	0.007

[1] Max steaming refers to the maximum speed that a vessel can steam at.

[2] Min Viable Gross refers to the minimum catch value per day that a fisher considers economically viable.

2.4.5. VMS and logbook data were linked to conjoint data to determine if modelled groupings related to differences in observed behaviours

Cluster 2 fishers recorded trips that were characterised by significantly higher departure distances, landings, duration, fuel use, and profit compared to the fishers in the other clusters (Table 2.4). However these fishers also recorded the lowest landed value of scallops per unit of fuel used (Value per Unit Fuel - VPUF); they were thus catching the most, but most inefficiently. Cluster 1 fishers spent the least time at sea, travelled the least distance, but still achieved the highest catch per unit effort (CPUE), profit per unit effort (PPUE), and VPUF. Cluster 2 showed the highest profit, but cluster 1 showed the highest catch rates and value per unit effort, suggesting that cluster 1 fishers were operating in a more efficient way. Fishers in cluster 3 recorded similar (or higher) CPUE values than cluster 2, but they stayed at sea for significantly less time, and recorded lower profits, nevertheless at a significantly higher VPUF. Cluster 3 fishers display a low CPUE and landings, but at a high VPUF, suggesting they either obtained a better price for their landings or were run at lower costs.

These patterns in logbook records matched some of the patterns identified in the conjoint analysis; for example cluster 2 fishers placed the highest importance on tow and meat quantity, and these were the fishers that caught the most. Cluster 3 fishers caught less and stayed at sea for less time, despite potentially having the ability to catch more (i.e. they achieved CPUE similar to cluster 2), but their VPUF was significantly higher, which could be consistent with their strategy identified in the conjoint analysis of targeting a higher quality product. Cluster 1 fishers recorded average catches, but at the highest CPUE, PPUE and VPUF. This is perhaps consistent with their conjoint analysis cluster, in which they placed a higher importance on the sea state and amount of cobble they would catch, i.e. they focussed more on attributes that influence the ease and efficiency of fishing rather than those directly affecting catches.

Table 2.4. GLM results to determine significant differences in logbook records between behavioural strategy clusters as identified in the conjoint analysis. Degrees of freedom vary where it was not possible to calculate a value in a logbook entry. PPUE = Profit per unit of effort.

Logbook Variable	DF	F	R-sq	P	Mean value per cluster			2-1		3-1		3-2	
					1	2	3	t	p	t	p	t	p
Departure Distance	2, 2167	$1.47e^5$	0.99	<0.001	10.5	11.3	11.8	3.11	0.002	3.8	<0.001	1.0	0.30
Scallop Value	2, 2157	$8.76e^{13}$	1	<0.001	1187	1401	1118	7.24	<0.001	-2.0	0.041	-6.5	<0.001
Hours at sea	2, 2170	295	0.21	<0.001	19.2	23.7	21.2	-23.9	<0.001	-9.0	<0.001	9.2	<0.001
Fuel Used	2, 2170	$3.8e^{12}$	1	<0.001	220	374	212	31.9	<0.001	-1.7	0.098	-19.8	<0.001
CPUE (per tow[1] hours)	2, 2170	$5.5e^8$	1	<0.001	103.9	98.36	95.1	-2.19	0.029	-2.88	0.004	-0.99	0.32
CPUE (per active[2] hours)	2, 2158	$6.6e^8$	1	<0.001	77.8	68.3	68.5	-5.76	<0.001	-4.61	<0.001	0.08	0.93
Profit	2, 2157	13.04	0.01	<0.001	1046	1165	982	-4.25	<0.001	1.89	0.059	4.66	<0.001
PPUE (per active hours)	2, 2157	27.47	0.02	<0.001	113.6	95.0	100.3	6.90	<0.001	4.08	<0.001	-1.38	0.168
PPUE (per tow hours)	2, 2157	11.29	0.01	<0.001	150.4	133.4	138.3	4.43	<0.001	2.60	0.009	-0.91	0.37
Wind speed	2, 2170	$1.80e^5$	0.99	<0.001	18.5	19.2	18.8	1.68	0.093	0.503	0.62	-0.75	0.454
VPUF	2, 2157	$6.04e^4$	0.98	<0.001	5.63	3.76	5.34	-16.39	<0.001	-1.99	0.047	11.6	<0.001
CPUE (per dredge hour)	2, 2170	$2.16e^6$	0.99	<0.001	17.5	14.3	16.7	-8.31	<0.001	-1.58	0.114	4.93	<0.001

[1] tow hours = time spent towing

[2] active hours = time spent towing + time spent steaming

2.4.6. By comparing the differences in the data types, three behavioural strategies were identified

By comparing the differences in the conjoint analysis, questionnaire responses, and logbook entries, three behavioural strategies could be identified; fishers with larger more powerful vessels that are most concerned with maximising the quantity and meat quality of catches (cluster 2 – quantity maximisers); efficient fishers with mid-sizes vessels who place a higher than average importance of sea state and amount of cobble when deciding where to fish (cluster 1 – efficient fishers); and smaller, less powerful, potentially less economically driven fishers, who place a higher than average importance of roe on scallops (cluster 3 – quality maximisers) (Table 2.5).

Table 2.5. Description of behavioural strategies determined from the conjoint analysis, questionnaire responses, and VMS and logbook data.

	Cluster 1	Cluster 2	Cluster 3
Conjoint analysis	Higher than average importance of sea state and cobble habitats	Higher than average importance of tow quality and meat yield.	Higher than average importance of roe on scallop
Questionnaire data	Smaller vessels than cluster 2, but not statistically significantly smaller than cluster 3 vessels. Same gross requirements as cluster 2, but significantly lower steaming speed and lower fuel use.	Largest vessels (by VCU), which travelled fastest, and used the most fuel.	Smallest vessels, with lowest tonnage, and crew members. Lowest economic targets.
VMS and logbook data	Average catch values, but travel least distance and have highest CPUE, PPUE, VPUF, and $CPUE_{perdredge}$	High distances travelled, value landed, trip duration, fuel used, and profit, but with lowest VPUF and $CPUE_{perdredge}$.	Least time at sea, lowest value of scallops landed and lowest profit – but at a higher VPUF than cluster 2.
Description of behavioural strategy	Large vessels with mid-range power (VCU), who consider more external patch variables such as sea state, cobble and distance to port, rather than purely the catch rates. Attain the best catch rates, fishing most efficiently.	Largest most powerful vessels, potentially most economically driven, targeting the quantity of scallops and the meat yield, i.e. aiming for a large volume catch, with high meat content.	Smaller, less powerful vessels, who catch less scallops and stay at sea for less time, targeting a higher quality product, who are potentially less economically driven.
Number of Vessels	7	3	4
Behavioural Strategy	Efficient Fisher (EFF)	Quantity Maximiser (QTM)	Quality Maximiser (QLM)

2.4.7. Comparison of Questionnaire and Conjoint Responses

The responses given in the questionnaire interview were compared to the results derived from the conjoint analysis, to see if similar responses emerged from these two independent data sources, providing some validation of the accuracy of responses. During the questionnaire fishers were asked what the maximum sea state was that would prevent them from fishing. The responses given are indicated as a red histogram on the plot of the utility scores (Figure 2.6a). There is a consistent agreement between where the sea state utility begins to fall and where it reaches its minimum utility with the range of values provided during the interviews. This provides confidence that the range of sea states which begin to hinder fishing activity were successfully identified. The response to distance to port is not quite as clear cut as the response to sea state. The questionnaire responses for maximum distance to port (red histogram) appear to be at the lower end of the values identified in the conjoint analysis (Figure 2.6b). Figure 2.6c shows the overlap between distances from port observed in the VMS data (histogram), and the range of distances identified in the questionnaire (red) and conjoint analysis (blue). The conjoint analysis appears to have better identified the distances at which the trip frequencies decline. The range of maximum distances from the questionnaire survey overlap a larger proportion of observed trip distances, which could suggest some fishers have underestimated the distances they travel, or could reflect individual heterogeneity in responses.
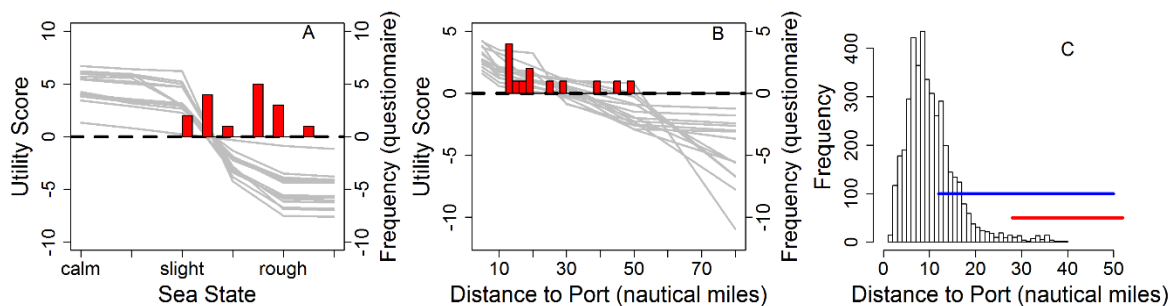
*Figure 2.6. Conjoint utility scores for sea state **(A)** and distance to port **(B),** with the number of questionnaire interview responses overlaid as red histograms corresponding to 'the sea state above which you would no longer fish' and the 'maximum distance you would travel from port in a fishing trip' respectively. Bars fall between sea states listed on the x axis when a fisher responded with a range, e.g. force 4-5, plotted as force 4.5. **C)** Histogram of distance to port values derived from logbook data, with a red line indicating the range between which conjoint utility scores first fall below zero and the upper limit where all conjoint utility scores are below zero. Blue line indicates the range of distances identified in the questionnaire as the 'maximum distance to port' fishers would travel in a single fishing trip.*

2.4.8. Validation of Questionnaire and Conjoint Responses

Both aggregated and individual responses to questions were verified against the independent VMS and logbook data. Fishers provided values for hours spent at sea, distance travelled, the catch rate at which they would move fishing ground, and the minimum viable catch value for a trip, which could all be compared to the observed values in VMS data. At an aggregated level, the questionnaire responses appear to give similar responses to the logbook data for departure distances, landings, and catch rates (Figure 2.7). The hours at sea responses appear to slightly underestimate the actual time spent at sea, however. The accuracy of each individual's questionnaire responses was assessed by comparing them to their own VMS and logbook data (Figures 2.8). Boxplots display each logbook variable for each individual fisher, and their corresponding questionnaire responses were overlaid as points. If the questionnaire response (point) falls in an appropriate place in the boxplot (e.g. at the lower range of the catch value boxplot for minimum viable catch) it provides evidence of the reliability of the questionnaire responses. This validation is somewhat qualitative, as the questions were somewhat subjective and/or speculative. The individual comparison data showed that fishers fairly consistently provided a minimum viable catch value in the lower quartile of the observed value landed, and a good takings value in the upper quartile (Figure 2.8a). The catch rates that a fisher considered as good, average or poor appear relatively consistent with their recorded catch rates (Figure 2.8c). The catch rates given in the questionnaire can therefore be considered as relatively accurate. In general the values given for normal hours at sea fall within the observed trip lengths (Figure 2.8b); the maximum possible trip length values appear quite variable, but as this is a speculative answer perhaps more variation is expected. Similarly, the departure distances given in the survey appear reasonably accurate, although slightly higher, with the more speculative maximum departure distance exhibiting more variation (Figure 2.8d).
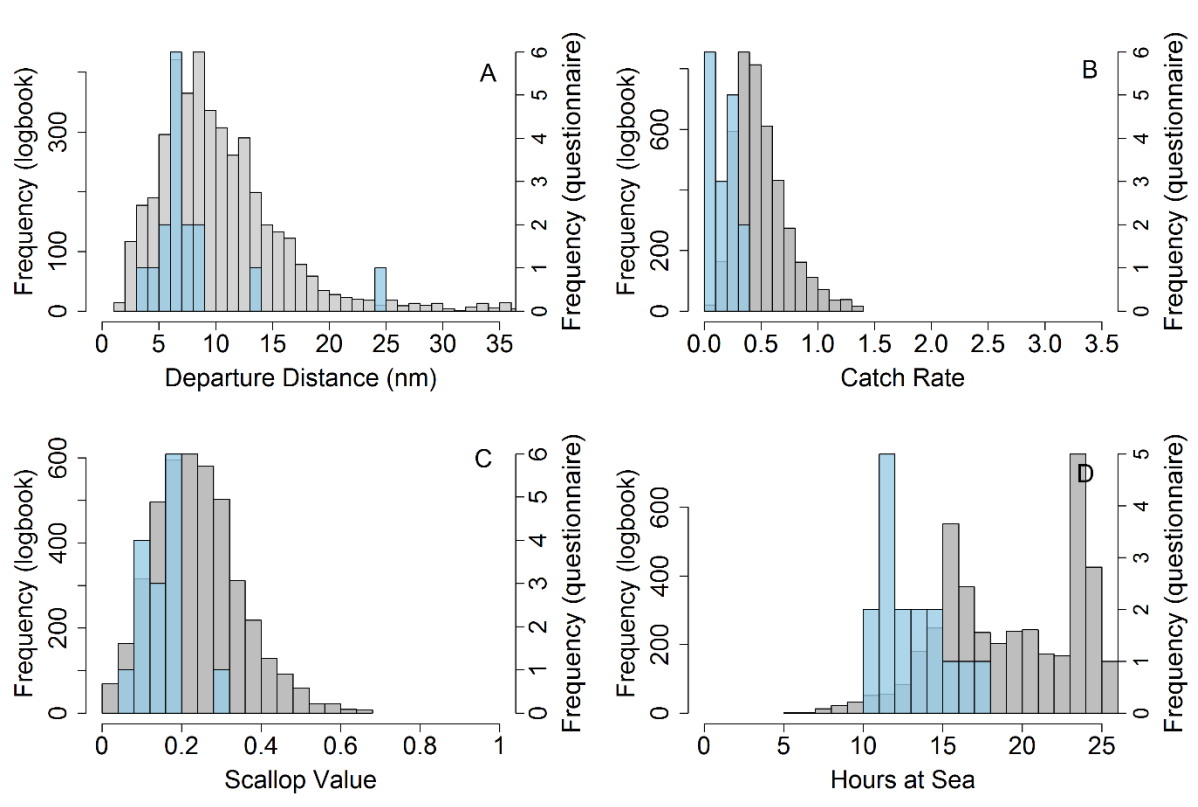
*Figure 2.7. Grey histograms represent logbook data for all scallop logbook records from Isle of Man vessels. Blue overlaid histograms represent questionnaire data. **A)** Grey histogram of departure distances from VMS data, with blue histogram indicating individual answers to 'What is the normal distance you would travel from your departure port to fish?' **B)** Grey histogram of recorded catch rates, as bags per dredge, with blue histogram indicating answers to 'At what catch rate would you change fishing location?' **C)** Grey histogram of the value of scallops landed per trip, and blue histogram of answers to 'What is the minimum viable catch for a trip? Values are scaled from zero to one for confidentiality. **D)** Grey histogram of trip length in hours at sea from VMS data, and blue histogram of answers to 'How long would you normally fish for?'*
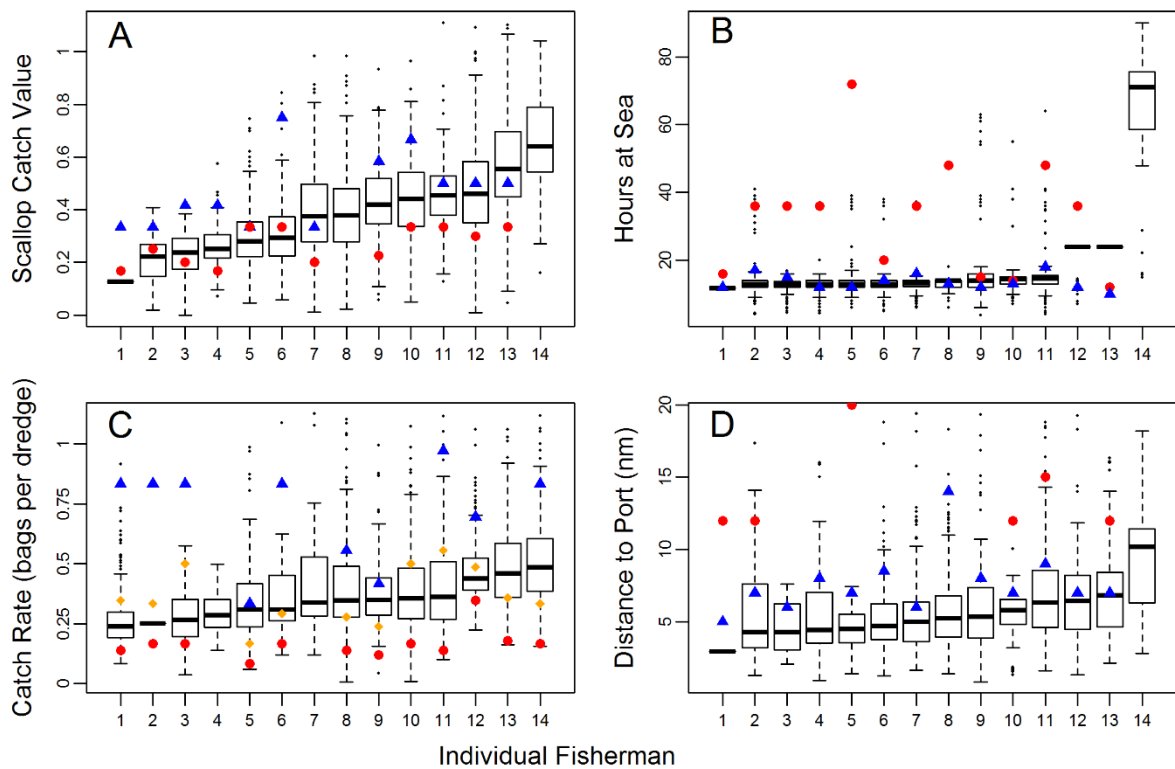
*Figure 2.8. Verification of individual questionnaire responses with vessel monitoring system (VMS) and logbook data. Boxplots represent VMS and logbook values for each individual fisher, and coloured dots represent their corresponding questionnaire responses. The number of points vary where a fisher did not provide a response to a question. Actual values of catch value and rates are concealed for confidentiality, with a scaled response presented. **A**). Boxplots of observed scallop landings (monetary value, from logbooks). Red points represent answer to the question "What is your minimum viable daily catch?", and blue points represent answers to the question "What do you consider as "good takings" for a trip?" **B)** Boxplots of observed trip length (hours at sea, from logbook). Blue point represents "How long would you normally fish for?" and red point represents "What is the maximum time you would spend at sea during one trip". **C)** Boxplots of observed catch rates (bags per dredge hour, from VMS), with corresponding value provided for question "What do you consider a good catch rate (blue) an average catch rate (orange) and a poor catch rate (red)?" **D)** Boxplots of observed departure distances (nautical miles, from VMS). Blue points represent "What distance would you normally travel from port to fish?", red points represent "What is the maximum distance from port you would travel to fish?"*

2.5. Discussion

2.5.1. Fishers' data can increase understanding of fishing behaviours and patch choice decisions

This study demonstrated that data derived directly from fishers can improve the understanding of fishing behaviour, and provide relevant and reliable data that could be used to parameterise a fisheries behavioural model. Using a conjoint analysis approach it was possible to gain a comprehensive understanding of the fishing decisions that drive patch choice and explain the behaviours that lead to patterns in the spatial distribution of fishing effort. As Plagányi et al., (2014) pointed out, it is the human decisions of patch choice that drive the spatial distribution of effort, therefore to model a fishery realistically it is necessary to understand these decisions. For example, the study demonstrated that the sea state can have a large influence on patch choice behaviour, therefore it may be necessary to include this in a model predicting fisher behaviour. It is also interesting to note that the term 'average' had different connotations to the respondents; an average tow quality had a positive utility score but an average meat yield had a negative utility score. Understanding these trade-off decisions is not possible with VMS data; a conjoint analysis provided a rapid, cost-effective way to understand this patch choice behaviour. It was also possible to gain insights into the degree of individual heterogeneity, which may be needed for more realistic predictions of the impacts of management on fishers (Christensen and Raakjær, 2006; Gelcich et al., 2005).

The accompanying semi-structured questionnaire provided further behavioural parameters that would be relevant to modelling fishers in the context of optimal foraging theory (i.e. fishing costs, environmental limitations, vessel characteristics and requirements). These data again represented parameters that would be difficult or impossible to obtain from vessel monitoring system data. As well as collecting vessel characteristic data that were not recorded on vessel registry data, behavioural parameters such as the giving up rate (a catch rate that a fisher considers unviable and would prompt him to move to a different fishing patch), and the handling time (the time it takes to clear nets between successive tows) could be collected. Economic parameters (the equivalent of animal energetics in optimal foraging theory) could also be ascertained, including vessel costs, what a fisher considered their minimum viable catch and what they considered as good takings. These survey data significantly contribute to, and increase the scope for understanding fisher behaviour, complementing the use of VMS and logbook data.

2.5.2. Considerable behavioural heterogeneity between fishers could be used to identify different fishing strategies

There was considerable behavioural heterogeneity between the fishers surveyed; vessel capacity units (a composite size metric) and vessel length were identified as predictors of this variability. As VCUs are calculated from length, and therefore correlate, only one or the other would be used for predictive modelling. Some economic variables demonstrated strong correlation with vessel size, such as fuel use, what they consider good takings, as well as vessel characteristics such as number of dredges used, and number of crew. Other variables showed no correlation with vessel size despite being linked to potential financial returns, e.g. the catch rate at which a fisher would 'give up' and move to a new location. These foraging parameters, and their heterogeneity, could be input to a model of their behaviour.

Three behavioural strategies for patch choice could be identified within the fleet, by comparing the similarities and differences in conjoint analysis responses. As identified in Table 2.5, fishers could be categorised as either Efficient Fishers (EFF), Quantity Maximisers (QTM) or Quality Maximisers (QLM). EFF refers to fishers that are the most efficient, in that they achieve the highest CPUE (by time and per dredge), PPUE, and VPUF, by travelling least far but still receiving average catches. These fishers place a higher than average importance on the sea state and the amount of rock in the catch, and are thus maximising efficiency by avoiding unfavourable fishing patches. These EFF fishers are also perhaps minimising risks and costs associated with taking vessels into high seas or over damaging rockier habitats. QTM fishers are the largest and most powerful vessels, concerned with maximising the quantity and meat quality of catches, obtaining the highest profits, but they do so at the lowest VPUF and $CPUE_{perdredge}$ rates. QLM refers to fishers with the smallest vessels who target a higher quality product (i.e. roe on), who achieve a $CPUE_{perdredge}$ equal to EFF fishers, yet land lower catches and have the lowest profit. QLM fishers have the potential to catch as much as EFF fishers (i.e. similar vessel characteristics, and achieve similar CPUE rates per dredge hour). They also obtain similar CPUE rates to QTM fishers despite their larger size. Nevertheless, they do not stay at sea as long, record lower catches, and state a significantly lower minimum viable catch rate, which could suggest the QLM fishers are less economically driven.

The identification of a group of fishers who are less economically driven, or just not as economically successful as the others, has consequences for a model based on optimal foraging theory, where individuals are modelled as rational agents (i.e. taking the course of action that will provide the highest fitness/monetary returns). Whilst optimal foraging theory may be an appropriate framework within which to investigate fishing behaviour, a model of fishing behaviour may need to include

fishers that do not follow the assumptions of optimal foraging theory to realistically predict the activity of a whole fleet. The general principles of optimal foraging theory may hold true in a fishery – that fishers are maximising their 'fitness' – but it may be necessary to allow the model to incorporate other non-monetary aspects of this fitness such as quality of life, through a reduced propensity to maximise purely the economic returns. Modelling all individuals as true optimal foragers may thus overestimate the stock biomass removal, as well as the ability of fishers to cope with management measures. For example, during a period of stock collapse and strict management controls in the Isle of Man in 2014, the fishers demonstrated considerable heterogeneity in their plasticity in response to tough conditions. Some fishers continued to fish on seemingly unprofitable grounds, with ground familiarity and port affinity apparently overriding the seemingly more rational choice of moving to a more distant port/ground (pers. comm., Karen McHarg, Department for Environment, Food, and Agriculture, Isle of Man). There may be several reasons a fisher does not move to a more profitable ground despite having the vessel capacity to do so: i) they are unfamiliar with the grounds, which represents an economic and safety consideration; ii) they are not aware that there are better catch rates at a different area nearby; iii) they are less economically driven and would simply *prefer* to remain at their usual port; iv) they are not profit maximisers and instead aim for a minimum expected yield (Oostenbrugge et al., 2001; Pet-Soede et al., 2001). For an accurate model of fishing behaviour it is necessary to capture these differences in competitiveness/success, and the influences of ground familiarity, as the fishers which are seen as less economically driven may not conform to a model that assumes solely profit driven rational activity. It is unclear from the data presented here, however, if the fishers are just less successful than others, if the fishers are intentionally not as economically competitive preferring to fish in familiar areas, or if they are maximising some other benefit, such as quality of life, more highly than monetary returns. Nonetheless, to reach agreeable management solutions that ensure the economic sustainability of a fishery, it may be necessary to understand these behaviours, so that they can at least be taken into consideration in management planning.

2.5.3. Survey data were validated to give confidence in the accuracy of the data

The data obtained during the questionnaire and conjoint analysis showed a good level of agreement with vessel monitoring system and logbook data, demonstrating that the fisher survey data can be considered reliable. The validation is somewhat qualitative however, as whilst quantitative responses were given, several questions were somewhat subjective (e.g. what do you consider as

good takings?). Nevertheless, responses to similar questions in the questionnaire and the conjoint analysis showed good correlation, giving confidence that the methods were eliciting realistic values. More compellingly, the questionnaire responses also showed good correlation with corresponding VMS and logbook data, on both an aggregated and individual vessel level. The values given for departure distance appeared to be reasonably accurate, concentrated over the highest proportion of observed travel distances in the VMS data; the minimum acceptable bags per dredge hour appeared to be a very consistent and reliable value; the values for minimum viable catch were slightly skewed towards the lower end of observed catches, as you would expect if the fishery is profitable, but it does suggest a proportion of trips may be considered unviable. The hours at sea values provided by fishermen were skewed towards more negative values than the VMS and logbook data however. On an individual scale, values provided during the questionnaire showed a good level of congruence with each individual's corresponding VMS and logbook data. Overall, these data suggest that in the absence of VMS and logbook data, behavioural data of a reasonable accuracy could be obtained from fishers.

The behavioural clusters identified in the conjoint analysis could also be somewhat verified through comparing them with questionnaire and logbook data. Behavioural differences identified in the conjoint analysis translated to real differences in observed behaviours in the VMS and logbook data. For example, fishers that placed the highest importance on expected return rates and meat yield in the conjoint analysis demonstrated higher catch rates and landings in logbook data accordingly. These patterns give confidence that the conjoint analysis has successfully identified real differences in the patch choice behavioural strategies of different fishers.

There are, nevertheless, two potential types of inaccuracy relevant to this survey data: deliberate bias and unintentional inaccuracy. Economically and industry sensitive data, such as catch rates and values, are most likely known well by the fishers, but they could be wary of revealing them to scientists, and therefore deliberately bias responses. Economic parameters were shown to be of good accuracy, which could give confidence that less sensitive parameters were also accurate to the best of the fishers' knowledge. If fishers were unhappy to give any response or value, they could leave it blank, as having missing values was considered preferable to inaccurate values. It would be difficult for respondents to deliberately bias answers in the conjoint analysis, as it is not easy to quickly compute how to skew the responses to an agenda. A final source of error is misrepresentation of the fleet. Even though a relatively high proportion of the fishery was surveyed (56%), it is likely some individual heterogeneity was missed. As over half of the active fishers were surveyed though, this gives some confidence that there was a fair representation of the fishery (Shepperson et al., 2014).

This survey approach to parameterising an IBM is the first step in a participatory modelling framework. Taking a more participatory approach can provide a form of mutual validation between fisher and scientist with regards to modelling fisher behaviour realistically. Scientists can be more confident they have captured the essential elements of the fishery, and have a realistic portrayal of fishing behaviour, and fishers can have more confidence that the scientists are basing their model on informed fisheries data. As described by Mackinson et al. (2011) and Röckmann et al. (2012), involving fishers in the modelling process can increase the transparency of the project and thus the trust of data and model outputs, leading to more successful management plans. Nevertheless, there does remain some scepticism among the scientific community as to whether fishers' data can be of comparable accuracy to more conventional scientific data. It is thus important to provide an assessment of data accuracy from all steps of the participatory process where possible, to ensure appropriate use of the data, and to contribute to the growing body of evidence showing that fisher knowledge and participatory data can make a valuable contribution to conventional science (Bundy and Davis, 2013; Shepperson et al., 2014; Teixeira et al., 2013; Zukowski et al., 2011).

2.5.4. This approach provided data relevant to parameterising a fisheries IBM

The data obtained in this survey are highly relevant to parameterising a fisheries behavioural model, both in terms of model design and understanding of fishing behaviour. Grouping fishers into types could allow simplification of a model design, which accounts for some heterogeneity between fishers without leading to an overly complex model design. Three behavioural strategies for patch choice were identified in the conjoint analysis, which could be specified in an IBM of fishing activity. The impact of management on different types of fishers could then be explored, as fishers may be impacted to different degrees. VCU was the best predictor of foraging parameters, behavioural strategy and vessel economics, and therefore could be used to characterise a fishery for proportional input of fishers of each behavioural strategy into a model. Characterising the fishery in this way could simplify the model design, whilst ensuring heterogeneity in fishing behaviour is accounted for.

The survey time could be considered as a limitation to the approach, but these surveys were undertaken in a relaxed informal format, with fishers free to lead the discussion onto topics they felt relevant. The survey time could therefore fairly easily be reduced. Depending on the computer literacy of the fishing fleet in question, the conjoint analysis could be fielded online, as could the

questionnaire, allowing fishers to complete the survey in their own time, and reducing the time costs to the researcher.

2.6. Conclusions

The use of a conjoint analysis has demonstrated in detail how fishers assess various patch attributes such as sea state, distance to port and expected catch rates, to decide which patch they would prefer to fish in. This could have direct application to a fisheries (or other hunter-gatherer) behavioural model. Further, the data also demonstrated behavioural heterogeneity, in that either some fishers are not as economically driven, or are less successful, as they do not appear to be reaching their full catching potential, compared to other similar fishers. Individual-based models (IBMs) are increasingly recognised as potentially useful management models in fisheries (Bastardie et al., 2014, 2010; Dowling et al., 2012), but they can be data intensive, as a thorough understanding of the behavioural decisions driving a system is required. Here this study has demonstrated an accurate and cost-effective method to collect the necessary data required to parameterise a fisheries IBM in the context of optimal foraging theory. Using this approach could make a model more relevant to a fishery through ensuring the behavioural decision processes are realistic (Fulton et al., 2011; Hilborn, 2007). Through developing models in collaboration with fishers, we can be more confident we have a realistic and thorough understanding of the system, and can thus better predict the outcomes of management. Better, more realistic predictions of the temporal and spatial displacement of effort following management would allow the economic and ecological impacts to be better understood, ultimately leading to more successful and sustainable management.

2.7. Acknowledgements

2.8. References

Abernethy, K.E., Allison, E.H., Molloy, P.P., Côté, I.M., 2007. Why do fishers fish where they fish ? Using the ideal free distribution to understand the behaviour of artisanal reef fishers. Canadian Journal of Fisheries and Aquatic Sciences, 11: 1595–1604.

Akaike, H., 1973. Information theory as an extension of the maximum likelihood principle. B.N. Petrov, F.Csaki (Eds.), Second International Symposium on Information Theory, Akademiai Kiado, Budapest (1973), pp. 267 – 281.

Alriksson, S., Öberg, T., 2008. Conjoint Analysis for Environmental Evaluation A review of methods and applications. Env. Sci. Pollut. Res., 15: 244–257.

Bastardie, F., Nielsen, J.R., Andersen, B.S., Eigaard, O.R., 2010. Effects of fishing effort allocation scenarios on energy efficiency and profitability: An individual-based model applied to Danish fisheries. Fisheries Research, 106: 501–516.

Bastardie, F., Nielsen, J.R., Miethe, T., 2014. DISPLACE: a dynamic, individual-based model for spatial fishing planning and effort displacement — integrating underlying fish population models. Canadian Journal of Fisheries and Aquatic Sciences, 71: 1–21.

Bergmann, M., Hinz, H., Blyth, R., Kaiser, M., Rogers, S., Armstrong, M., 2004. Using knowledge from fishers and fisheries scientists to identify possible groundfish "Essential Fish Habitats." Fisheries Research, 66: 373–379.

Bucaram, S.J., Hearn, A., 2014. Factors that influence the entry–exit decision and intensity of participation of fishing fleet for the Galapagos lobster fishery. Marine Policy, 43: 80–88.

Bucaram, S.J., White, J.W., Sanchirico, J.N., Wilen, J.E., 2013. Behavior of the Galapagos fishing fleet and its consequences for the design of spatial management alternatives for the red spiny lobster fishery. Ocean & Coastal Management, 78: 88–100.

Bundy, A., Davis, A., 2013. Knowing in context: An exploration of the interface of marine harvesters' local ecological knowledge with ecosystem approaches to management. Marine Policy, 38: 277–286.

Cabral, R.B., Geronimo, R.C., Lim, M.T., Aliño, P.M., 2010. Effect of variable fishing strategy on fisheries under changing effort and pressure: An agent-based model application. Ecological Modelling, 221: 362–369.

Christensen, A.-S., Raakjær, J., 2006. Fishermen's tactical and strategic decisions. A case study of Danish demersal fisheries. Fisheries Research, 81: 258–267.

Clarke, K., Gorley, R., 2006. PRIMER v6: User Manual/Tutorial. PRIMER-E, Plymouth.

Dowling, N. a, Wilcox, C., Mangel, M., Pascoe, S., 2012. Assessing opportunity and relocation costs of marine protected areas using a behavioural model of longline fleet dynamics. Fish and Fisheries, 13: 139–157.

Fulton, E. a, Smith, A.D.M., Smith, D.C., van Putten, I.E., 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Gelcich, S., Edwards-Jones, G., Kaiser, M.J., 2005. Importance of Attitudinal Differences among Artisanal Fishers toward Co-Management and Conservation of Marine Resources. Conservation Biology, 19: 865–875.

Green, P., Srinivasan, V., 1990. Conjoint analysis in market research: a review of new developments. Journal of Marketing, 54: 3–19.

Grimm, V., Railsback, S.F., 2005. Individual-Based Modeling and Ecology. Princeton University Press, Princeton.

Hadjimichael, M., Kaiser, M.J., Edwards-Jones, G., 2013. The impact of regulatory obligations on fishers' income: Identifying perceptions using a market-testing tool. Fisheries Research, 137: 129–140.

Hallwass, G., Lopes, P.F.M., Juras, A. A, Silvano, R. a M., 2013. Behavioral and environmental influences on fishing rewards and the outcomes of alternative management scenarios for large tropical rivers. Journal of Environmental Management, 128: 274–82.

Hilborn, R., 2007. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Kraak, S.B.M., Kelly, C.J., Codling, E. A, Rogan, E., 2010. On scientists' discomfort in fisheries advisory science: the example of simulation-based fisheries management-strategy evaluations. Fish and Fisheries, 11: 119–132.

Kruskal, W.H., Wallis W.A., 1952. Use of ranks in one-criterion variance analysis. Journal of the American Statistical Association, 47(260): 583 – 621.

Lee, J., South, A.B., Jennings, S., 2010. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES Journal of Marine Science, 67: 1260 – 1271.

Mackinson, S., Wilson, D.C., Galiay, P., Deas, B., 2011. Engaging stakeholders in fisheries and marine research. Marine Policy 35, 18 – 24.

Mackinson, S., Wilson, D.C.K., 2014. Building bridges among scientists and fishermen with participatory action research, in: Social Issues in Sustainable Fisheries Management MARE Publication Series Volume 9. pp. 121–139.

Murray, L.G., Hinz, H., Kaiser, M.J., 2011. Functional response of fishers in the Isle of Man scallop fishery. Marine Ecology Progress Series, 430: 157 – 169.

Nelder, J., Wedderburn, R., 1972. Generalized Linear Models. Journal of the Royal Statistical Society. Series A, 135 (3): 370 – 384.

Oostenbrugge, J. a. E. Van, Densen, W.L.T. Van, Machiels, M. A. M., 2001. Risk aversion in allocating fishing effort in a highly uncertain coastal fishery for pelagic fish, Moluccas, Indonesia. Canadian Journal of Fisheries and Aquatic Sciences, 58: 1683–1691.

Orme, B. 2010. Getting started with conjoint analysis: Strategies for product design and pricing research. Second Edition, Madison, Wis. Research Publishers LLC.

Pascoe, S., Gréboval, D., (eds.), 2003. Measuring capacity in fisheries. FAO Fisheries Technical Paper. No. 445. Rome, FAO. 2003. 314p.

Pet-Soede, C., Van Densen, W.L.T., Hiddink, J.G., Kuyl, S., Machiels, M. A. M., 2001. Can fishermen allocate their fishing effort in space and time on the basis of their catch rates? An example from Spermonde Archipelago, SW Sulawesi, Indonesia. Fisheries Management Ecology, 8: 15–36.

Plagányi, É.E., Punt, A.E., Hillary, R., Morello, E.B., Thébaud, O., Hutton, T., Pillans, R.D., Thorson, J.T., Fulton, E. a, Smith, A.D.M., Smith, F., Bayliss, P., Haywood, M., Lyne, V., Rothlisberg, P.C., 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries, 15: 1–22.

R Core Team, 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austra. https://www.R-project.org/.

Railsback, S.F., 2001. Concepts from complex adaptive systems as a framework for individual-based modelling. Ecological Modelling, 139: 47–62.

Reeves, S., Marchal, P., Mardle, S., Pascoe, S., Prellezo, R., Thebaud, O., Travers, M., 2009. From Fish to Fisheries: The Changing Focus of Management Advice, in: Payne, A., Cotter, J., Potter, T. (Eds.), Advances in Fisheries Science: 50 Years on from Beverton and Holt. Blackwell Publishing Ltd, Oxford, UK.

Röckmann, C., Ulrich, C., Dreyer, M., Bell, E., Borodzicz, E., Haapasaari, P., Hauge, K.H., Howell, D., Mäntyniemi, S., Miller, D., Tserpes, G., Pastoors, M., 2012. The added value of participatory modelling in fisheries management – what has been learnt? Marine Policy, 36: 1072–1085.

Ruiz-Pérez, M., Franco-Múgica, F., González, J. a., Gómez-Baggethun, E., Alberruche-Rico, M. a., 2011. An institutional analysis of the sustainability of fisheries: Insights from FishBanks simulation game. Ocean & Coastal Management, 54: 585–592.

Sawtooth Software Inc., 2014. The Adaptive Choice-Based Conjoint (ACBC) Technical Paper.

Sawtooth Software Inc., 2009. The CBC/HB System for Hierarchical Bayes Estimation Version 5.0 Technical Paper.

Shepperson, J., Murray, L.G., Cook, S., Whiteley, H., Kaiser, M.J., 2014. Methodological considerations when using local knowledge to infer spatial patterns of resource exploitation in an Irish Sea fishery. Biological Conservation, 180: 214–223.

Soulié, J.-C., Thébaud, O., 2006. Modeling fleet response in regulated fisheries: An agent-based approach. Mathematical and Computer Modelling, 44: 553–564.

Teixeira, J.B., Martins, A.S., Pinheiro, H.T., Secchin, N.A., Leão de Moura, R., Bastos, A.C., 2013. Traditional Ecological Knowledge and the mapping of benthic marine habitats. Journal of Environmental Management, 115: 241–50.

Thébaud, O., Doyen, L., Innes, J., Lample, M., Macher, C., Mahévas, S., Mullon, C., Planque, B., Quaas, M., Smith, T., Vermard, Y., 2014. Building ecological-economic models and scenarios of marine resource systems: Workshop report. Marine Policy, 43: 382–386.

Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environmental Modelling and Software, 25: 1268–1281.

Wattage, P., Mardle, S., Pascoe, S., 2005. Evaluation of the importance of fisheries management objectives using choice-experiments. Ecological Economics. 55, 85–95.

Wilen, J.E., 1979. Fisherman Behavior and the Design of Efficient Fisheries Regulation Programs. Journal of the Fisheries Research Board of Canada, 36: 855 – 858.

Wilen, J.E., 2006. Why Fisheries Management Fails: Treating Symptoms Rather than the Cause. Bulletin of Marine Science, 78: 529–546.

Wilen, J.E., Smith, M.D., Lockwood, D., Botsford, L.W., 2002. Avoiding Surprises: Incorporating Fishermen Behaviour into Management Models. Bulletin of Marine Science, 70: 553–575.

Yates, K.L., 2014. View from the wheelhouse: Perceptions on marine management from the fishing community and suggestions for improvement. Marine Policy, 48: 39–50.

Zukowski, S., Curtis, A., Watts, R.J., 2011. Using fisher local ecological knowledge to improve management: The Murray crayfish in Australia. Fisheries Research, 110: 120–127.

2.9. Appendix 1. Relationships between vessel size metrics and behavioural parameters

Variable	Length cor. Coeff	n	p	signif	VCU cor. Coeff.	n	p	signif
Engine Power	0.46	16	0.072	.	0.85	16	0.000	***
Tonnage	0.71	12	0.010	**	0.91	12	0.000	***
Average number of crew	0.84	16	0.000	***	0.86	16	0.000	***
Max number of dredges	0.7	16	0.003	**	0.85	16	0.000	***
Fuel use per towing hour	0.71	13	0.007	**	0.86	13	0.000	***
Normal departure distance from port	0.52	16	0.039	*	0.78	16	0.000	***
Max number of days at sea in relation to king scallop freshness	0.53	16	0.034	*	0.77	16	0.001	***
Minimum monthly gross required	0.68	5	0.204		0.98	5	0.004	**
Considered 'good takings'	0.69	16	0.003	**	0.66	16	0.006	**
Fuel use per steaming hour	0.7	13	0.007	**	0.7	13	0.008	**
Vessel fuel storage capacity	0.46	15	0.087	.	0.64	15	0.011	**
Max number of bags possible to store aboard	0.68	16	0.004	**	0.6	16	0.014	**
Cost of a days fishing	0.49	14	0.078	.	0.6	14	0.023	*
Average steaming speed (knots)	0.58	16	0.018	*	0.54	16	0.030	*
Time taken to clear king dredges	0.45	16	0.082	.	0.52	16	0.037	*
Bags per hour (queens) at which would move location the next	0.72	4	0.284		0.95	4	0.045	*
Minimum viable daily gross	0.37	16	0.164		0.49	16	0.052	.
Minimum daily gross worth fishing for	0.76	9	0.017	*	0.63	9	0.067	.
Max steaming speed (knots)	0.49	16	0.055	.	0.41	16	0.118	
Daily gross at which would consider leaving fishery	0.68	7	0.091	.	0.61	7	0.145	
Cost of boat upgrades in 5 year period	0.51	11	0.113		0.46	11	0.152	
Number of days a year lost to bad weather	-0.44	13	0.136		-0.39	13	0.185	
Absolute maximum sea state possible to fish in	0.34	16	0.205		0.34	16	0.194	
Max possible duration of a fishing trip	0.29	16	0.270		0.33	16	0.206	
Cost of boat maintenance per year	0.69	13	0.008	**	0.38	13	0.206	
Percentage of takings as wages	0.55	8	0.161		0.48	8	0.227	
Percentage of catch below MLS	-0.13	14	0.663		-0.34	14	0.236	
Max number of days possible at sea in relation to food supplies	-0.14	13	0.637		-0.34	13	0.249	
Max sea state would normally prefer not to fish above	0.28	16	0.285		0.3	16	0.255	
Average hours at sea fishing for king scallops	0.5	16	0.051	*	0.27	16	0.310	
Maximum distance travelled from port	0.45	14	0.103		0.25	14	0.390	
King catch rate at which would move location	0.15	16	0.578		0.23	16	0.400	
Considered 'too long' to spend at sea	-0.06	10	0.860		-0.3	10	0.407	
Maximum gape of trawl net	0.43	15	0.108		0.23	15	0.411	
Max number of days at sea in relation to queen catch freshness	0.18	16	0.503		0.21	16	0.435	
Max wave height possible to fish at	0.45	14	0.104		0.21	14	0.466	
Smallest distance willing to fish near another vessel (miles)	0.31	16	0.239		0.18	16	0.506	
Bag size (kg)	0.14	16	0.617		0.15	16	0.597	
How often information from other vessels is taken into account	-0.2	14	0.483		-0.13	14	0.667	
How much of fishing is in same area as past year	-0.39	16	0.131		-0.11	16	0.697	
Time taken to clear queen trawl nets	0.32	13	0.288		-0.11	13	0.720	
King dredge belly ring size	-0.13	14	0.657		-0.1	14	0.721	
Number of days a year lost to planned maintenance	0.09	14	0.765		0.09	14	0.758	
Minimum market price at which would fish (kings)	-0.55	8	0.160		-0.03	8	0.894	
Lowest monthly 'wage' below which would consider leaving	-0.02	4	0.984		-0.1	4	0.904	
Max number of days at sea in relation to fuel capacity	-0.11	15	0.398		0.03	15	0.904	
How many vessels would tolerate within 1nm radius	-0.15	13	0.621		0.03	13	0.920	
Minimum market price at which would fish (queenies)	-0.38	10	0.278		-0.02	10	0.956	
Catch per dredge hour at which would move location	0	16	0.990		0.01	16	0.960	
Catch per gape length at which would move location	-0.56	6	0.248		0.01	6	0.984	
Number of other vessels information shared with	0.21	16	0.442		-0.01	16	0.985	
Number of days lost to unplanned mechanical failure	0.34	13	0.249		0	13	0.992	

CHAPTER 3: Using VMS and Logbook Data to Inform the Development and Validation of an Individual-based Model

3.1. Abstract

The ability to predict the response of fishers to fisheries management would improve our ability to understand the consequences of management and to evaluate different management options. To model the behavioural response of fishermen to management we need to understand the behavioural decisions that drive the spatial and temporal distribution of fishing activity. An Individual-based Model (IBM) could be used to better understand fishermen's behaviour, through testing out different behavioural rules and structures, and allowing more realism in fishing behaviours. To develop an IBM, a good understanding of the behaviours in a system is required, to inform the model development, and to provide the data that can be used to validate a model.

VMS and logbook data were used to characterise spatial and temporal patterns in fishing activity in the Isle of Man scallop fishery. Fishing activity largely constituted single day trips within the 12nm territorial Sea, was concentrated over known grounds, and activity became more dispersed as the season progressed. A generalised linear mixed effects model was used to investigate the decision of whether or not to fish each day. The likelihood of fishing on a particular day was significantly influenced by the wave height, the days since the start of the season, previous catch rates, and predicted wave conditions. Whilst a rough sea state can prohibit fishing, vessels were not predicted to fish with 100% certainty on days with calm sea states. The analysis also highlighted heterogeneity between the abilities and requirements of individual fishing vessels. The patterns in VMS and logbook data were discussed in the context of qualitative information provided during questionnaire interviews with fishers.

Developing an IBM of fishing activity can have relatively substantial data requirements. This analysis demonstrated that VMS and logbook data can be used to characterise activity in a fishing system, providing information required to inform model development, and the values and patterns against which a model could be validated.

3.2. Introduction

It is increasingly recognised that in order to achieve successful fisheries management outcomes, it is beneficial to be able to predict how fishermen will respond to management (Dinmore *et al.*, 2003; Fulton *et al.*, 2011; Hilborn, 2007; Hilborn *et al.*, 2004; Murray *et al.*, 2011; Pascoe and Mardle, 2005). To model the behavioural response of fishermen to management we need to understand the behavioural decisions that drive the spatial and temporal distribution of fishing activity. Individual-based modelling could help address some of the knowledge gaps in our understanding of fisher behaviour, and allow us to better predict the environmental and economic consequences of management by more realistically accounting for the behavioural response of, and impact on, fishers (Burgess *et al.*, 2017, in review). Nevertheless, to create an individual-based model (IBM) of fishing behaviour, it is necessary to have a good understanding of the system, to inform the model development, and also to provide trends and patterns in the real system against which such a model can be validated (Grimm *et al.*, 2005).

3.2.1. Fishers are analogous to animal foragers under Optimal Foraging Theory

A number of authors have demonstrated that Optimal Foraging Theory (OFT) (MacArthur and Pianka, 1966) is a suitable framework for investigating fisher behaviour (Begossi, 1992; Begossi *et al.*, 2009; de Oliveira and Begossi, 2011; Lee *et al.*, 2014; Sosis, 2002). Optimal foraging theory states that individuals aim to maximise their net energy intake over time (analogous to catches or profit for a fisher), and is therefore comparable to assuming fishers follow profit maximisation behaviour (Holland, 2008). As fisher-target species systems can be considered analogous to animal predator-prey systems, operating in the same predictable context of optimal foraging, successful animal predator prey modelling techniques may be applicable to predicting fisheries dynamics. Successful individual-based models (IBMs) of bird behaviour constructed by Goss-custard *et al.* (2005) and Stillman (2008) were built around six main parameters; i) bird energetics; ii) prey energy content; iii) functional response; iv) interference functions; v) food supply, exposure time, weather; vi) human disturbance. Equivalent modelling parameters could also be derived for fisher systems. Bird fitness could be replaced by fisher economic status, prey energy content replaced by profit or CPUE, human activities replaced by management actions, and so on. Table 3.1 highlights the equivalence of variables in a bird foraging IBM compared with a fisheries IBM. To build a model of fishing behaviour in a similar foraging framework, it would therefore be necessary to understand the distribution of

foraging patches in the system, the costs associated with fishing and the rewards received, heterogeneity between individuals, and how they decide where to fish.

Table 3.1. ABM parameters required for a bird foraging model, and their equivalent parameter in a fishery ABM.

	Bird Foraging Model	Fishery Model
Foraging patches	Patches containing food birds need to consume to survive	Patches containing fish that vessels capture to increase financial income
Resting patches	Patches in which animals rest and do not / are not able to capture further prey	Patches (e.g. ports) in which vessels stay between fishing voyages
Natural variation/mortality in prey	Mortality of prey not caused by foragers	Mortality of fish not caused by fishers
Individual foragers	Individual animal	Individual vessel
Alternative resources	Alternative prey	Off sector pluriactivity / alternative target species
Size range of prey captured	Size range of prey that can be consumed	Size range of fish that can be landed legally
Value of resources	Amount of energy	Financial value
Condition of forager	Body mass determined by past values of energy assimilation	Financial status determined by past income and expenditure
Forager costs	Energetic costs of survival and moving between patches	Time and financial cost to move between fishing grounds and port
Forager travel costs	Time and energy taken to move between patches	Time and financial cost to move between fishing grounds and port
Forager rewards	Energetic rewards of prey	Financial rewards of fish
Individual variation between foragers	Animals vary in their ability at capturing prey and stealing prey from competitors	Vessels vary in their capture rate (vessel size/catching power, experience of crew)
Forager decision rules	Animal occupies patch and consumes prey that leads to maximum rate of energy assimilation	Fishing vessel occupies patch which yields the greatest rate of income accounting for capture rate, the financial cost of harvest, and financial cost of occupying fishing grounds.

3.2.2. Adding realism to an optimal foraging model of fishers

Despite being demonstrated as an appropriate framework, modelling fishers under the framework of optimal foraging theory can be subject to some unrealistic assumptions, namely: foragers have ideal knowledge of resource levels in each patch; foragers are able to move equally between all patches; and foragers have equal competitive abilities. In reality, this may not be the case; fishers may know estimates of resource densities, but cannot know exact values; larger vessels may have greater potential to travel further and more quickly between patches; and larger vessels may out-compete smaller vessels (Rijnsdorp et al., 2000). To realistically model fishing behaviour, it may be necessary to better understand these violations, such as heterogeneity between individuals and the differences in fishing capabilities (e.g. maximum distances they can travel, maximum sea states above which they wouldn't fish) and requirements (e.g. minimum viable catch rates). Developing an IBM of fishing behaviour could allow us to better understand fishing behaviour, and what processes it is important to consider when predicting the response to management.

3.2.3. Pattern Oriented Modelling to inform model development

IBMs are often developed using pattern oriented modelling (POM), which is essentially a protocol to build and evaluate individual-based models (Grimm *et al.*, 2005; Grimm and Railsback, 2012; Stillman *et al.*, 2015). POM describes a framework in which multiple patterns observed in the real system are used to guide model development and evaluation; models are then accepted or rejected based on their ability to reproduce these patterns (e.g. Railsback and Johnson, 2011). At the simplest level, these patterns tell us what individuals, spatial scales, and environments should be represented in the model, and the variables and processes characterising them (Grimm and Railsback, 2012). For example, if we know that in the real system there are differences in capabilities of individual fishers, individual variability should be included in the model. These patterns also form the criteria for model development and selection. In complex systems, using a single pattern (or value) is often not sufficient to reduce uncertainty in a model structure; using multiple patterns at different scales can reduce uncertainty (Grimm *et al.*, 2005). Ideally, patterns are selected that characterise the system at different levels and scales (e.g. daily catch rates, total catches over a season, spatial extent of fishing, individual variation); recreating multiple patterns at different scales suggests the behavioural mechanisms in the model are somewhat realistic (Grimm *et al.*, 2005).

3.2.4. Vessel monitoring system data can be used to investigate fishing activity

Patterns for model development can be derived from the literature, experts, existing theory, or empirical data (Grimm and Railsback, 2012). In Europe, vessel monitoring systems (VMSs) were introduced as an enforcement tool, but are increasingly important for scientific research into fishing activity (Lambert *et al.*, 2012; Murray *et al.*, 2011, 2013). VMS has some limitations, including sometimes incomplete coverage, and a relatively long temporal duration between position records (~ 2 hours). In addition, VMS does not record the activity being performed by a vessel (i.e. whether it is fishing or steaming), but this can be inferred from the speed a vessel is travelling (Lee *et al.*, 2010). VMS data and logbook data (detailing catches) can therefore be used to understand more about fishing behaviour, and to document patterns in fishing activity (Lee *et al.*, 2010; Murray *et al.*, 2011).

3.2.5. Aims

In this chapter, patterns in fishing activity in the Isle of Man scallop fishery were characterised using vessel monitoring system and logbook data, to inform the development of an individual-based model. Three questions were addressed: how much do fishermen catch, and when, and where do they catch it? This chapter aimed to: characterise the spatial and temporal distribution of effort in the IOM scallop fishery; analyse what influenced the decision of a vessel to fish or not each day; and outline individual heterogeneity in effort, behaviour, and catches. The analysis focussed on Manx fishing vessels within the 12nm territorial sea, but differences between Manx and non-Manx vessel activity (i.e. resident inshore vs more nomadic) were also outlined.

3.3. Methods

3.3.1. The Isle of Man Scallop Fishery
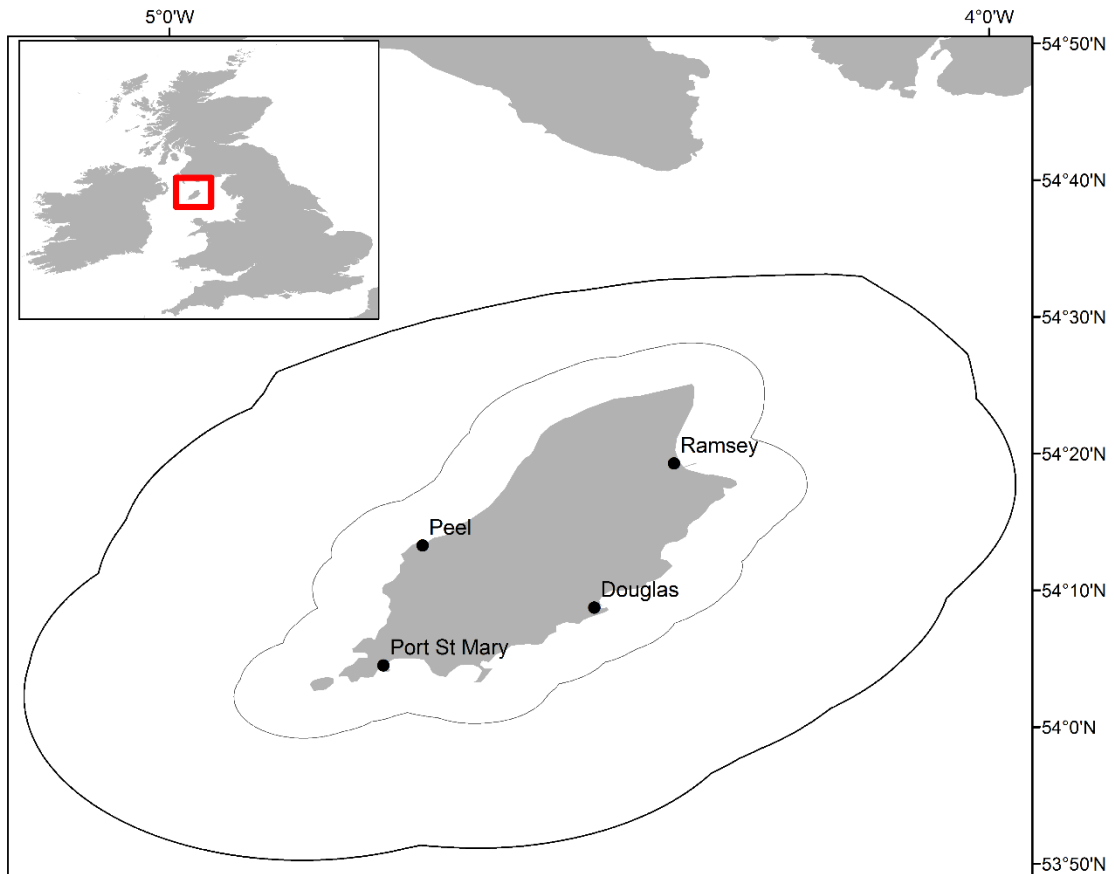
Figure 3.1. The Isle of Man, showing the 4 main fishing ports, with the 3nm and 12nm territorial Sea. The northerly part of the 12nm boundary is 'compressed' to the median line between the Isle of Man and Scotland which is less than 24nm in total.

King scallops (*Pecten maximus*) and Queen scallops (*Aequipecten opercularis)* have been important fisheries for the Isle of Man since the 1950s, and form the most valuable fishery for Manx (Isle of Man) vessels (Hanley *et al.*, 2013; Figure 3.1). Essentially the same vessels prosecute both fisheries, switching between the use of dredges for king scallops during the open season (November – May) and trawls for queen scallops at other times (June – October). The different fishing gears reflect the different life histories of the two species, with king scallops being more sedentary, burrowing into the sediment, whilst queen scallops are more active swimmers (Hanley *et al.*, 2013). This research focusses on the behaviour of scallop dredgers when targeting the more valuable king scallop fishery.

King scallops (hereafter referred to as 'scallops') are fished using toothed Newhaven dredges, which are each approximately 75cm in width, with around eight 110mm metal teeth along the front edge of the dredge. The dredge teeth rake up scallops from the seabed, which are collected in a mesh bag behind the tooth bar. Groups of dredges are positioned along a wheeled tow bar, which keeps the dredges at a constant height from the seabed and reduces drag. In Manx territorial waters, scallop dredgers are restricted to using ten dredges within 3nm from shore, and 14 dredges within 12nm from shore. The minimum landing size for scallops is 110mm at the widest point; small scallops are returned to the sea, although likely subject to some indirect fishing mortality (Gruffydd, 1972; Jenkins and Brand, 2001).

All vessels fishing for scallops in the Isle of Man territorial sea are required to carry a vessel monitoring system (VMS), which provides approximately two-hourly spatial position data on the vessel (GPS location) (note: this poll frequency was increased to 15 minutes in 2016/17). Vessels are also required to return daily logbook records of their catches per ICES sub-square. By joining the VMS position records with the logbook catch data, the resulting spatially resolved catch data can be used for scientific research into fishing activity (Lee *et al.*, 2010). This analysis focusses on activity within the 12nm territorial sea, as there is full VMS coverage for this area, and the majority of scallop fishing by Manx vessels takes place within that area.

3.3.2. Logbook and VMS Data Processing

VMS records for all vessels fishing in the IOM territorial sea were obtained for the time period 2011–2013. The data was first cleaned, to remove inaccurate and incorrect data. The *vmstools* package in R (Hintzen *et al.*, 2012) was used to remove VMS points that were on land, were duplicates, were too close together and classed as pseudo-replicates (i.e. < 5 minutes between two consecutive pings), or were travelling at an unfeasible speed (>20 knots). VMS data does not provide information on the activity of a vessel (i.e. if it is fishing or not) at the time a ping is recorded. However, using the speed of the vessel, the likely activity can be inferred given the known range of towing speeds associated with specific fishing gear (Lee *et al.*, 2010). Creating a frequency histogram of the vessel speeds recorded allowed outlier values to be identified, and the speeds identifying towing and steaming activity to be checked. The vessel speeds showed a bimodal distribution, with the first peak (at slower speeds) indicating towing activity and the second peak (at higher speeds) indicating steaming activity. Points with a speed between 1 and 4 knots were defined as 'towing' and points with a speed over 4 knots were recorded as 'steaming'. Points with a speed below 1 knot that were located over fishing grounds (delineated by being within 1km of another fishing point) were also

recorded as 'towing' as these were likely when vessels were relatively stationary and hauling or emptying dredges, but performing activities associated with towing. Points with a speed below 1 knot that were not over fishing grounds were recorded as inactive (e.g. anchored, not fishing).

VMS and logbook records were merged according to the vessel reference number and the date, such that VMS position records that fell within the date and time of a logbook record were attributed to that logbook record (Hintzen *et al.*, 2012). VMS points are recorded approximately every 2 hours, although the frequency can change. To calculate the time spent towing and time spent steaming from the number of VMS points which indicate each activity, it was necessary to calculate the time period accounted for by one VMS point. For each logbook entry, the time between the first and last point was divided by the total number of VMS points recorded for that logbook entry. This gave a value for 'time per point'. Therefore, if a vessel fished for 10 hours, with 10 points, each point was equivalent to 1 hour of activity. The number of points denoting towing activity and the number of points denoting steaming activity could then be multiplied by the 'time per point', to give the time spent towing and time spent steaming within that logbook entry.

3.3.3. Calculating catch per unit effort

The calculation of Catch per Unit Effort (CPUE) allowed a standardised value for catch that could be compared between fishing trips of different effort. Effort can be defined in many ways, such as distance, time or power; in this case, time was used for effort, as we were interested in how fishermen allocated their activity over time. CPUE was calculated as:

$$CPUE_{fishing} = landings \text{ / } time \text{ } spent \text{ } fishing$$

CPUE, as described above, provides a standardised catch rate over time. However, it does not account for the difference in catching power of each vessel. A value for CPUE per dredge hour provides a value that can be directly compared across trips and vessels. However, the number of dredges a vessel used is not recorded in VMS or logbook data, but we can estimate it from the size of the vessel, from an equation constructed using questionnaire data (Shepperson et al., 2016, Chapter 2). Data were obtained from the vessel registry on the length, breadth, engine capacity, and vessel capacity unit of vessels. The vessel capacity unit (VCU) provided a comparable unit of power based on the size and capacity of the vessel. The number of dredges per vessel showed a significant correlation with VCU ($F_{(1, 14)}$ = 35.53, Adj R-sq = 0.70, p<0.001), and thus the number of dredges per vessel could be estimated using the equation:

Number of dredges = 0.019 (VCU) + 2.984

CPUE$_{dredge}$ could then be calculated as:

CPUE$_{dredge}$ = CPUE $_{fishing}$ / number of dredges

3.3.4. Removal of outlier values

A frequency distribution of the calculated CPUE illustrated that there were some erroneous values. The maximum CPUE value was 1149kg per hour which suggested that vessels were catching around 33 bags per dredge per hour, which is logistically unfeasible. These inaccurate values could be due to: human error when recording the logbook landings entry; an error in the VMS data treatment, e.g. points classed as steaming that should have been classed as fishing; or an error in VMS data itself (e.g. missing points), either through a technical fault in the VMS, or by a vessel travelling outside the area for which VMS was received. Nevertheless, these anomalous and/or incorrect values were removed from the analysis. To objectively remove outlier values, a lognormal or gamma distribution was fitted to variables using Akaike's Information Criterion to select the best fit between distributions, and values in the top 0.1% of this distribution were removed as outliers (Table 3.2).

Table 3.2 Outliers were removed from the catch data according to the following distributions, resulting in only a small overall proportion of points being removed

Variable	0.999 quantile distribution	Threshold Value	Proportion removed	Points Remaining
CPUE per fish hour (kg)	gamma	404.68	0.0024	19378
CPUE per dredge per hour (bags)	normal	0.74	0.0028	17354
CPUE per dredge per hour (kg)	gamma	30.88	0.0024	17433
Scallops landed (kg)	lognormal	8120.84	0.0005	23712
Scallops Value (£)	lognormal	12038.63	0.0001	23669
Value per unit fuel (VPUF)	gamma	20.76	0.0013	17593

3.3.5. Trip Distance

The trip distance and distance to port were calculated for each trip. A cost distance raster was created in R that calculated the travel distance from each Manx port (Peel, Douglas, Ramsey, and Port St Mary) to all locations in the 12nm Sea accounting for the land (i.e. not a linear distance). VMS points were then attributed with a value for the distance travelled from their departure port. To

calculate the trip distance, the furthest distance between the departure port and a VMS point for each logbook entry was taken.

3.3.6. Environmental Data

Hindcast wave height data was available to use which coincided with the 2011 VMS and logbook data (Neill et al., 2014). Wave height values at a 3km grid resolution were joined to the VMS position data such that each VMS position record was attributed with the day's average wave height at that position. Wind data was obtained from the Ronaldsway Meteorological office in the Isle of Man containing wind speed and direction values at 1-hourly intervals. The overall average daily wave height and average daily wind speed were correlated, but nevertheless average wind speeds between $10 - 40\text{km}^{-1}$ could relate to an average wave height of 1m (Figure 3.2). Depending on the wind direction some areas of the island would be sheltered and others exposed. An average wind speed of 20kmph related to wave heights of $0 - 2$m experienced by vessels fishing, and vessels fishing in conditions of 1m wave height were related to average wind speeds of around $10 - 40$kmph. A high wind speed does not necessarily translate as high wave heights in all areas, e.g. due to a shorter fetch in sheltered areas closer to the coastline. Using an average wind speed for the whole island may therefore not account for sufficient spatial variation in sea conditions around the island; it would be better to use the spatial wave height data where possible. Analysis relating to the decision of when to fish therefore used only 2011 VMS and logbook data with the 2011 wave data.
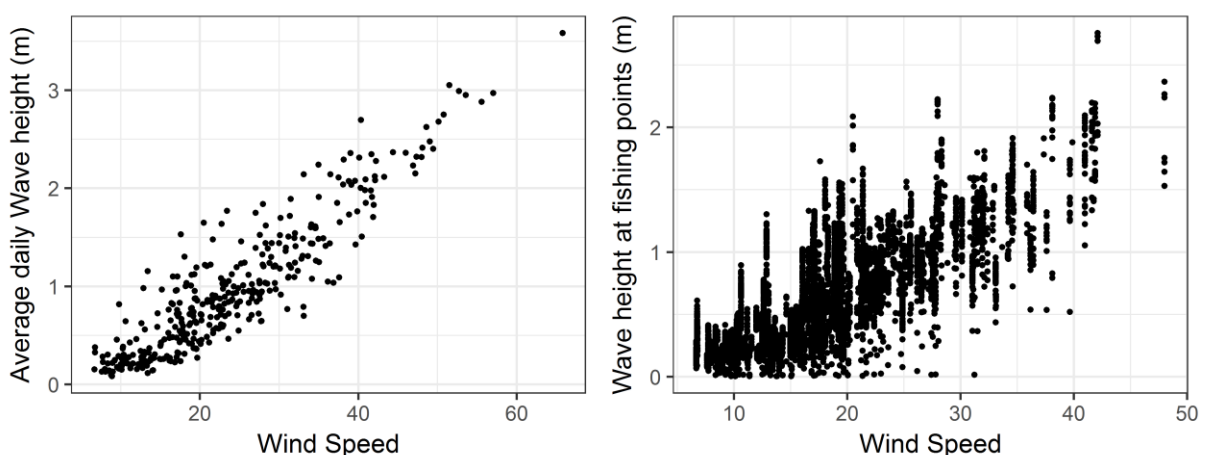
Figure 3.2. The relationship between the A) average wind speed and average wave height recorded each day in the Isle of Man and B) the average wind speed and the wave heights experienced by vessels fishing in the Isle of Man. There is high variability in the wave heights recorded at fishing points, as vessels can normally find shelter somewhere around the island, so some vessels will experience lower than average wave conditions.

3.3.7. Basic Economic Data

Fuel consumption per tow hour and per steaming hour were significantly correlated with VCU (per tow hour $F_{(1,11)}$ = 29.98, Adj R-sq = 0.71, p<0.001; per steam hour $F_{(1,11)}$ = 10.65, Adj R-sq = 0.45, p<0.01) (Shepperson *et al.*, 2016; Chapter 2). Equations for fuel consumption per towing hour and fuel consumption per steaming hour were thus derived per vessel VCU:

Fuel consumption per tow hour = 0.146 (VCU) - 0.808

Fuel consumption per steam hour = 0.142 (VCU) + 4.358

The amount of fuel used per trip could then be estimated, accounting for differences in fuel consumption by size. Total fuel consumption was calculated as:

Total fuel consumption = (Fuel$_{tow}$ * Towing hours) + (Fuel$_{steam}$ * Steaming hours)

where Fuel$_{tow}$ is the fuel consumption per tow hour, and Fuel$_{steam}$ is the fuel consumption per steam hour. Total fuel cost can then be calculated as:

Total fuel cost = Total fuel consumption * Fuel price

Fishermen consistently stated that a third of the takings go to the crew wages, therefore a third of the scallop landings value was subtracted before the profits were calculated.

3.3.8. External Vessels

The term "External" vessel is used hereon to refer to any vessel which is not registered to the Isle of Man. External vessels are permitted to fish for scallops in the IOM territorial sea, provided they hold a licence to do so. To understand the fleet and fishery dynamics, and to model the activity of the fishery, it is necessary to have some understanding of whether and how the activity of the External vessels differs to that of the Manx vessels.

3.3.9. Data Analysis

The likelihood of a vessel fishing or not on each day was estimated using a generalised linear mixed effects model (GLMM) implemented in the package *lme4* in R (Bates *et al.*, 2015; Zuur *et al.*, 2009). The binary response variable was whether or not a vessel fished on a particular day. A binomial error

distribution was used. The number of days since the start of the season, the wave height, the last day's catch for that vessel, the average wave height over the next week, and the total catch over the previous 2 weeks for that vessel were added as fixed effects, with by-vessel random slopes and intercepts for the effect of wave height.

Variables were scaled to reduce the effects of different scales of variables (e.g. wave height values of 0-4, catch values of 0 – 6000) (Table 3.3). The wind speed, the average wave height over the next 14 days, the vessels average catch over the last week, and the next day's average wave height were removed from the model using variance inflation factors (VIFs; selecting so that all VIFs < 2) to reduce collinearity. Individual vessels were included as a random effect, to control for non-independence, as the responses of each individual are more likely to be correlated with each other, compared to responses from another individual. Models with and without a random component were compared to determine the influence of including a random effect. Akaike's Information Criterion (AIC) was used to select the optimal model structure, estimated with a maximum likelihood fit. This showed that including individual vessels as a random effect improved the model fit, and that all fixed effects should be included in the final model. The final model was re-fit using restricted maximum likelihood (REML) criterion.

Table 3.3 Treatment of Variables included in the model. Grey shaded rows indicate variables omitted due to collinearity.

	Scaled	Removed due to VIF	Model Term
Wave height	Y		Fixed effect
Number of days since start of season	Y		Fixed effect
Last day's catch for that vessel	Y		Fixed effect
Average wave height over the following week	Y		Fixed effect
Total catch over previous 2 weeks	Y		Fixed effect
Individual vessel			Random slope and intercept
Wind speed	y	Removed	
Average wave height over following 2 weeks	Y	Removed	
Vessel's average catch over the last week	Y	Removed	
Next day's average wave height	y	Removed	

In the context of pattern oriented modelling (POM), a pattern is a "defining characteristics of a system" or "anything beyond random variation" (Grimm *et al.*, 1996, 2005). A pattern could refer to the spatial distribution of fishing activity, trends in catches over time, the variability in catches between vessels, or simply a qualitative description that vessels prefer one ground to another.

Throughout the results, the term 'pattern' is therefore used to refer to any characteristic of the system that a model could be compared to.

3.3.10. Questionnaire Data

Sixteen Manx fishermen were interviewed to understand fishing behaviour in the Isle of Man scallop fishery. Numerical results were presented in Chapter 2; results from the VMS and logbook analysis in this chapter are discussed in the context of more qualitative information provided by fishers during these interviews (Chapter 2; Shepperson *et al.*, 2016).

3.4. Results

A total of 4903 scallop dredging logbook entries were recorded by Manx vessels during the king scallop fishing seasons (1st November – 31st May) in years 2011, 2012, and 2013. Catches were recorded by 29 vessels during this period; the vessels ranged in size from 9.84m to 18.25m registered length. Over the three studied years, 3500 tons of scallops were recorded in landings, with a value equivalent to approximately £4.6 million. Manx vessels recorded a total of 133344 VMS position records over the study period, 119183 of which were classed as fishing activity, which could be linked to 4374 logbook records. Non-Manx vessels recorded 5969 logbook entries and 187089 VMS position records, landing 6600 tonnes of scallops, valued at £9.5 million. The following analysis used only Manx vessel data, until section 4.8 where a comparison between Manx and External vessels is presented.

3.4.1. Trends in Fishing Effort and Landings

Manx scallop vessels operate primarily as day trips (trips are essentially restricted to one day in length with a curfew), with 97% of logbook records displaying single day trips, and 81% of trips landing catches in the same port they had departed from. There was spatial variation in activity and catches, with vessels travelling furthest but catching least at Ramsey, whilst Port St Mary had the highest ratio between average travel distance and average landings (Table 3.4). Consequently, Port St Mary had the highest value per unit fuel consumed, and Ramsey the lowest. During a questionnaire survey (Shepperson *et al.,* 2016; Chapter 2), the average minimum viable catch per dredge hour was reported as 6.7kg per dredge per hour. This suggests that the fishers in the Isle of Man scallop fishery may be operating close to the limits of what the fishers consider as economically viable, as the mean experienced catch rate is below this rate at two of the grounds. This could also suggest some reluctance of vessels to move to a different port / ground where they may achieve better catch rates.

Table 3.4. Mean values per trip, with standard error, leaving from each port, and fishing over each ground. Fishing grounds: CHI = Chickens, EDG = East Douglas, POA = Point of Ayre, TAR = Targets

	Ports				Fishing Grounds			
	Douglas	Peel	Port St Mary	Ramsey	CHI	EDG	POA	TAR
Scallops landed (kg)	718.7 ± 9.9	695.5 ± 8.8	853.6 ± 10.9	491.9 ± 9.5	863.08 ± 9.2	639.15 ± 8.0	681.53 ± 87.1	619.03 ± 10.3
CPUE (kg per dredge hour)	6.26 ± 0.09	6.03 ± 0.07	7.49 ± 0.09	4.78 ± 0.08	7.44 ± 0.08	5.64 ± 0.07	7.09 ± 0.66	5.35 ± 0.07
Departure Distance (km)	23.64 ± 0.19	23.14 ± 0.15	16.06 ± 0.22	35.13 ± 0.22	19.21 ± 0.20	27.42 ± 0.22	32.01 ± 1.49	23.69 ± 0.21
Fuel Used	277.67 ± 3.52	269.02 ± 2.37	251.54 ± 2.48	244.83 ± 2.99	263.31 ± 2.17	263.81 ± 2.66	248.40 ± 23.10	262.84 ± 3.14
Profit	1035.7 ±16.4	985.9 ± 13.1	1209.1 ± 16.2	744.6 ± 16.7	1209.13 ± 13.71	912.27 ± 13.02	1218.13 ± 192.39	871.38 ± 15.58
Value per unit fuel	4.67 ± 0.07	4.42 ± 0.05	5.61 ± 0.07	3.73 ± 0.07	5.41 ± 0.06	4.28 ± 0.05	5.71 ± 0.78	4.08 ±0.07
Number of trips	1070	1780	1068	791	1558	1557	26	1101

3.4.2. The temporal distribution of effort

Vessels exhibited a preference towards fishing at locations or times with lower wave heights (Figure 3.3a); the distribution of the wave heights experienced by fishing vessels (red) is more skewed towards smaller wave heights than the distribution of all wave heights modelled (blue). The response to wave height is heterogeneous, however; some vessels appeared to show more avoidance of higher wave heights than others (Figure 3.3b). Fishers stated during a questionnaire that they would not fish above an average wave height of 2.45m (Shepperson *et al.,* 2016, Chapter 2), which is reflected in Figure 3.3a and 3.3b. The average wave height around the whole island was only above 2.45m on 9 days in the 2011 scallop fishing season (4%). The average wave height per ground was over 2.45m on 19 days at Chickens, 14 days at East Douglas, 6 days at Point of Ayre, and 9 days at Targets, representing 9%, 7%, 3% and 4% of the 212 days available for fishing (i.e. in the open season) respectively. The maximum wave height per day recorded anywhere around the island was over 2.45m on 58 days, however. The maximum wave height per ground was over 2.45m on 55 days at Chickens, 48 days at East Douglas, 39 days at Point of Ayre, and 47 days at Targets, representing 26%, 23%, 18% and 22% of the 212 possible scallop fishing days respectively.
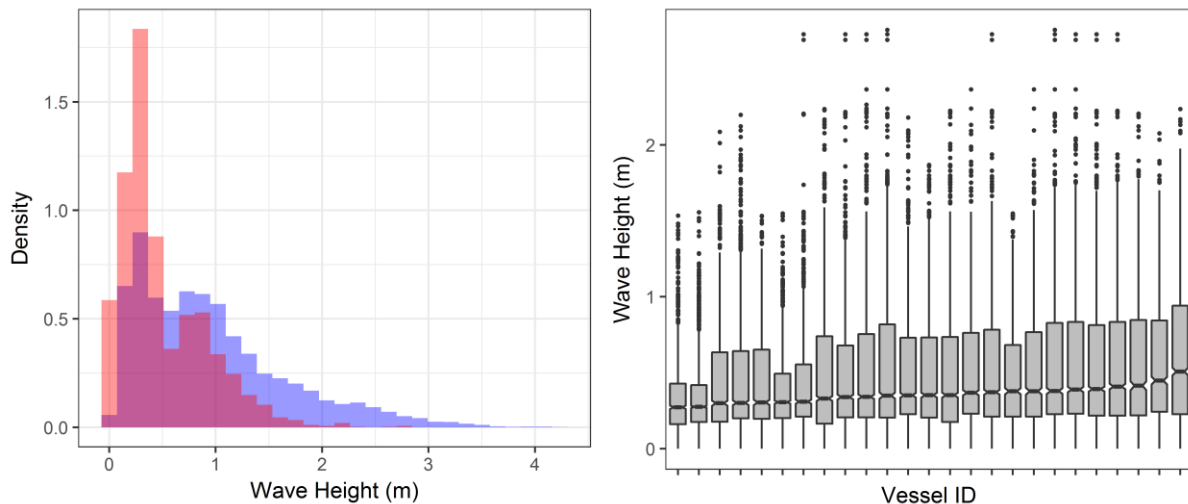
Figure 3.3. A) Wave heights at all grid points throughout 2011 (blue), wave heights recorded at all VMS points (red), and overlap in the distributions displayed as purple. B) The wave heights experienced by each vessels.

Sea conditions may determine whether a vessel is or is not physically able to fish on a particular day, but there may be other internal state variables, such as previous catches, that further influence the decision to fish. A mixed effects binomial model was used to analyse the probability of fishing on a given day. The optimal structure included a random intercept and slopes, indicating that the response differed between individuals (Table 3.5). As expected, as the wave height increased, the likelihood of fishing decreased (Figure 3.4). A typical vessel had around a 40% probability of fishing on a day with no waves, but this probability fell as wave height increased, with a near zero probability of fishing once waves reached over 2m average height, which was reflected in the questionnaire responses (Shepperson *et al.,* 2016, Chapter 2). Wave height therefore plays an important role in determining whether a vessel will fish or not, but having a calm sea state does not mean all Manx vessels will fish in Manx waters all of the time. There was also considerable variability between individual vessels, with some vessels very likely to fish in good conditions, and others very unlikely to fish even if conditions were good (Figure 3.5). Similarly, as the season progressed, the likelihood of fishing decreased, but there was variation between individual fishers. When catches were high, a vessel was highly likely to fish again the next day, but if catches were low, they were much less likely to fish the following day (Figure 3.4). If catches fell below 4000kg the likelihood of fishing again the next day declined. There was also variability in this response, with some vessels likely to fish again at lower catch rates than others (Figure 3.5). More long term variables, the previous 2 weeks catch, and the predicted wave heights for the following week, had a much weaker influence on the likelihood of fishing (Figure 3.4).
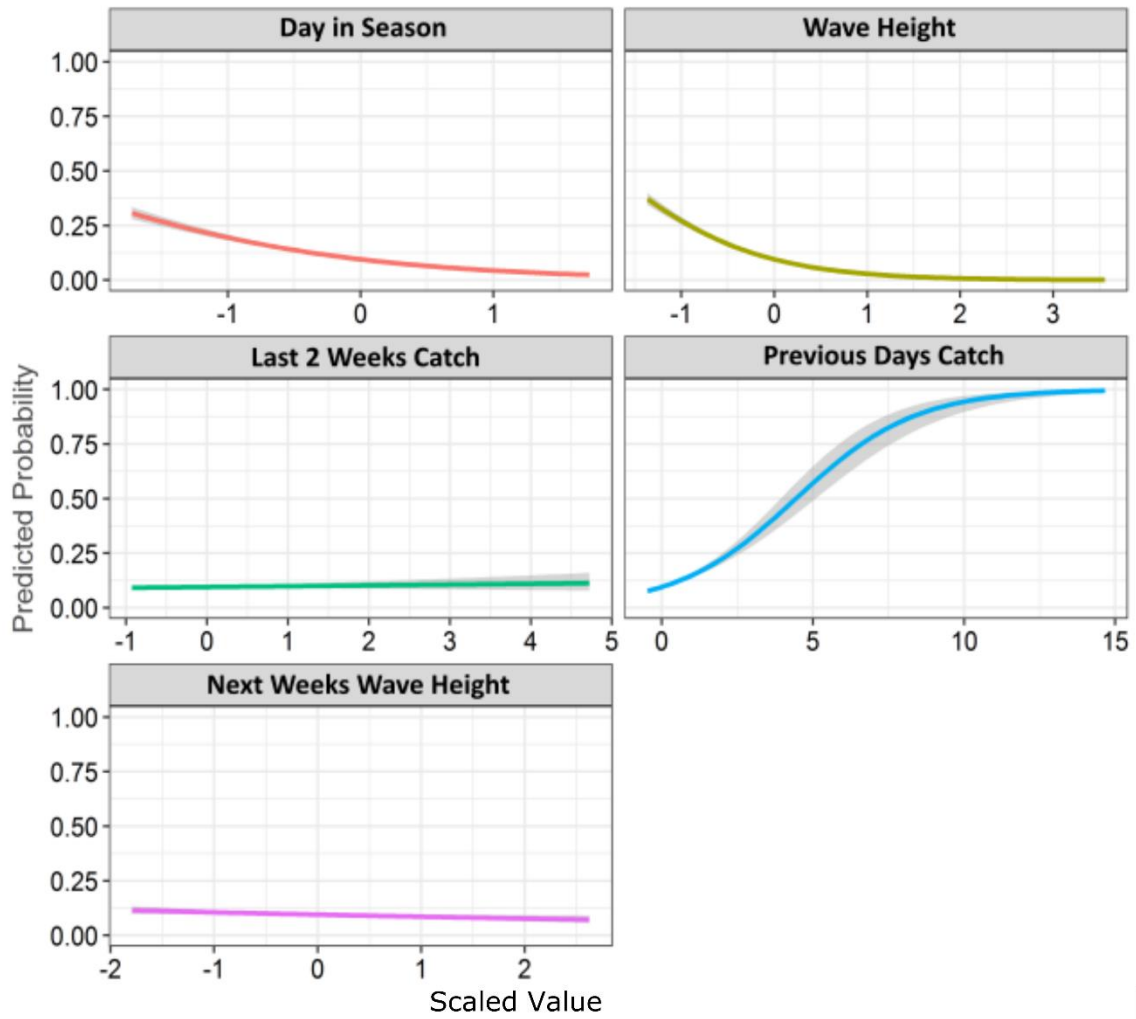
Figure 3.4. The average probability of a vessel fishing each day, predicted by the fixed coefficients, using a binomial mixed effects model with a random slope and intercept for each individual fisher.
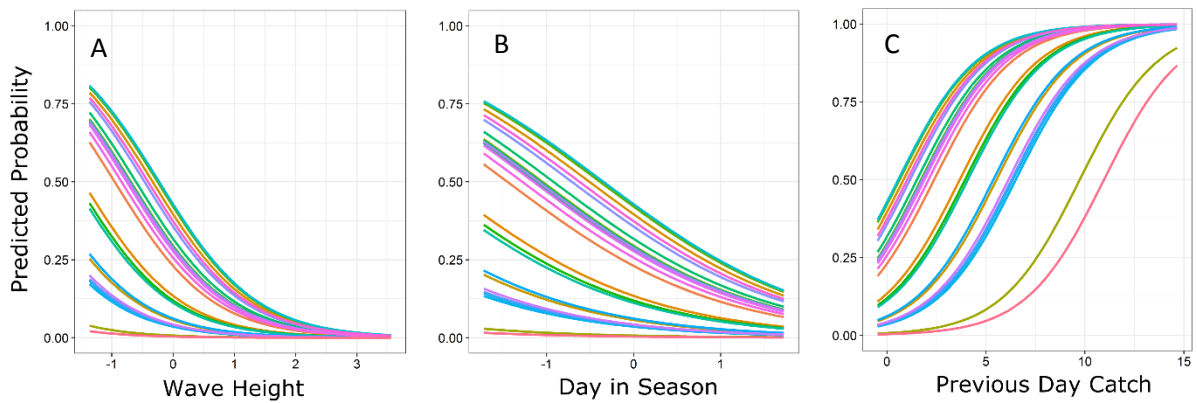
Figure 3.5. The predicted probability of fishing explained by wave height (A), days since the start of the season (B), and previous day's catch (C), for each individual vessel (random effect).

Table 3.5. Comparison of model 1 (no wave height data, random slope and intercept), model 2 (wave data, random intercept only), and model 3 (wave data, random slope and intercept)

	Model 1 (No wave height fixed effect, random slope and intercept)			Model 2 (Random intercept)			Model 3 (Random slope and intercept)		
	B	se	p	B	se	p	B	se	p
Fixed Parts									
Intercept	0.04	0.010	<0.001	0.25	0.03	<0.001	0.25	0.03	<0.001
Wave height	-	-	-	-0.13	0.005	<0.001	-0.13	0.02	<0.001
Day in Season	-0.08	0.005	<0.001	-0.08	0.005	<0.001	-0.08	0.005	<0.001
Previous day catch	0.10	0.005	<0.001	0.11	0.005	<0.001	0.10	0.005	<0.001
Previous 2 weeks catch	0.02	0.006	<0.001	0.02	0.006	0.003	0.02	0.006	<0.001
Next week wave height	-0.02	0.005	<0.001	-0.02	0.005	0.001	-0.02	0.005	0.001
Random Parts									
N_{vessel}	29			29			29		
ICC_{vessel}	0.349			0.134			0.144		
Observations	6159			6159			6159		
AIC	4298.291			4575.454			4269.990		

3.4.3. The Spatial Distribution of Effort

Manx vessels operating from the Isle of Man fish primarily within the 12nm territorial sea; 79% of trips took place completely inside the 12nm territorial sea (i.e. all VMS points for a trip were inside the 12nm boundary), 21% of trips were mainly within the 12nm Sea (i.e. over half of VMS points for a trip were inside the 12nm boundary), and <1% of trips recorded more than half or all VMS points outside of the 12nm sea. Vessels preferred to fish at the ground closest to the port they departed from (Table 3.6). 93% of all trips departing from Port St Mary fished over the ground called Chickens, 92% of all trips from Douglas fished at East Douglas, and 86% of trips from Ramsey fished at East Douglas. From Peel there was more variation with 63% of trips at Targets, and 35% at Chickens; the port of Peel is located within similar distance from the two grounds. There is therefore a preference to fish at the grounds closest to the departure port.

The footprint of fishing (i.e. total extent of fishing activity) was relatively constant per year, with Manx vessels fishing in 48% of the area of the territorial sea in 2011, 54% in 2012, and 56% in 2013. At the start of the fishing season activity was concentrated over smaller spatial extents. In November 2011 32% of the area of the territorial sea was fished, 21% in December, 40% in Jan, 34% in Feb, 44% in March, 40% in April, and 24% in May. The concentration of activity at the start of the season may be due to vessels targeting the areas with the highest scallop densities, or due to the

harsher environmental conditions over the winter months restricting available patches. In November the wind direction was mainly from the south and east, and fishing activity was concentrated on the west of the island (Figure 3.7). In comparison, in December the prevailing winds were from the west, with wave conditions reaching over 2m at the south of the island. Consequently, fishing activity was clustered to the more sheltered eastern side of the island (Figure 3.7). Fishers also demonstrated 'fishing the line' behaviour (Goñi *et al.*, 2008), concentrating activity around the edge of closed areas (Figure 3.6), due to a real or perceived spill-over effect; depending on the spatial scale of a model, it may be necessary to account for this effect.

Table 3.6. Proportion of trips made from each port to each fishing ground. Fishing grounds: CHI = Chickens, EDG = East Douglas, POA = Point of Ayre, TAR = Targets

	CHI		EDG		POA		TAR	
	Number	%	Number	%	Number	%	Number	%
Peel	564	35.0	26	1.6	3	0.2	1017	63.2
Ramsey	13	2.0	556	86.2	21	3.3	55	8.5
Douglas	58	5.8	921	92.3	2	0.2	17	1.7
Port St Mary	923	93.3	54	5.5	0	0	12	1.2

Figure 3.6. Vessels concentrate activity around the borders of closed areas, known as 'fishing the line', due to a real or perceived spill-over effect. No geographic coordinates or land references are displayed, to maintain fisher confidentiality.
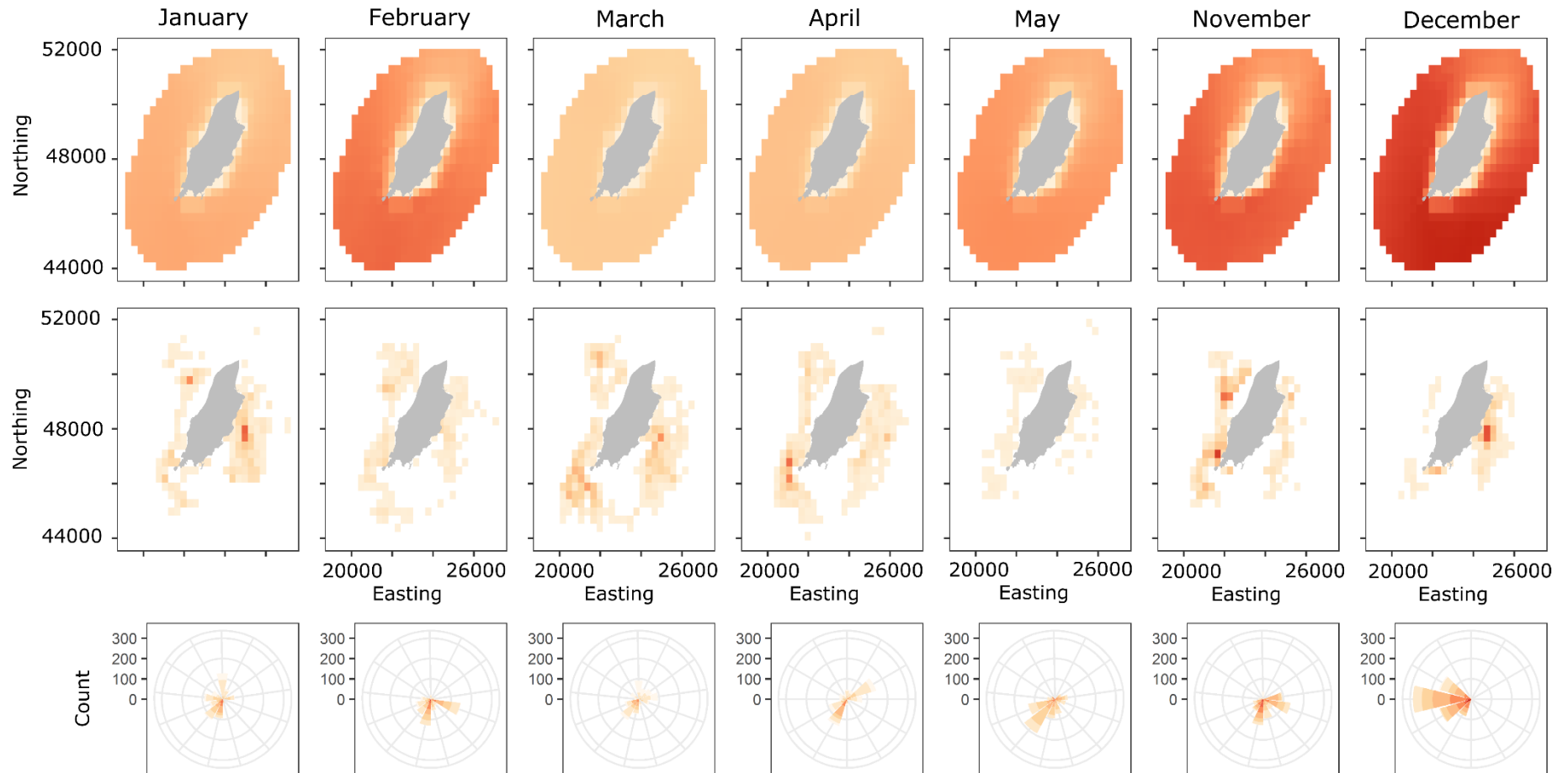
Figure 3.7. Wave heights, wind conditions, and fishing intensity around the Isle of Man, for each month in the scallop fishing season (Jan Feb Mar Apr May Nov Dec) in 2011. Row 1: Average monthly wave height in each 3km grid cell of the 12nm territorial Sea around the Isle of Man. Row 2: Concentration of fishing activity (VMS points) around the Isle of Man; no fishing took place in white areas. Row 3: Wind roses for average daily wind conditions, indicating the direction, strength, and frequency of wind conditions.

3.4.4. Individual heterogeneity in behaviour and catches

The total extent of fishing activity by each vessel varied, from under 1000km^2 (10% of the study area) to over 6000km^2 (68% of the study area), suggesting that some vessels have a stronger ground preference than others (Figure 3.8a). Generally vessels did not fish over a large extent during one fishing trip, remaining in a relatively small area (Figure 3.8b). The average extent of fishing points during one trip spread across 36km^2, which equates to 4 grid cells in a 3km grid. Nevertheless, some trips were more spread out, suggesting that vessels sometimes substantially changed location during a fishing trip. Two vessels displayed larger spread about their fishing points per trip, suggesting they were more likely to move location substantially (Figure 3.8c). Nevertheless, during 60% of all trips the towing took place in only 19km^2 (equivalent to 2 cells), in 70% of trips, 31km^2 (3 cells), in 80% of trips, 49km^2 (5 cells), and in 90% of trips in less than 88km^2 (10 cells), indicating that a day's fishing activity normally took place within a relatively small area (Figure 3.8d). Vessels also favoured certain fishing locations and fished these preferentially; 10 – 30% of each vessel's tows took place in only 1% of the studied area. The level of ground preference varied between vessels, with one vessel recording over 25% of all tows in only 10 grid cells (an area of 90km^2).
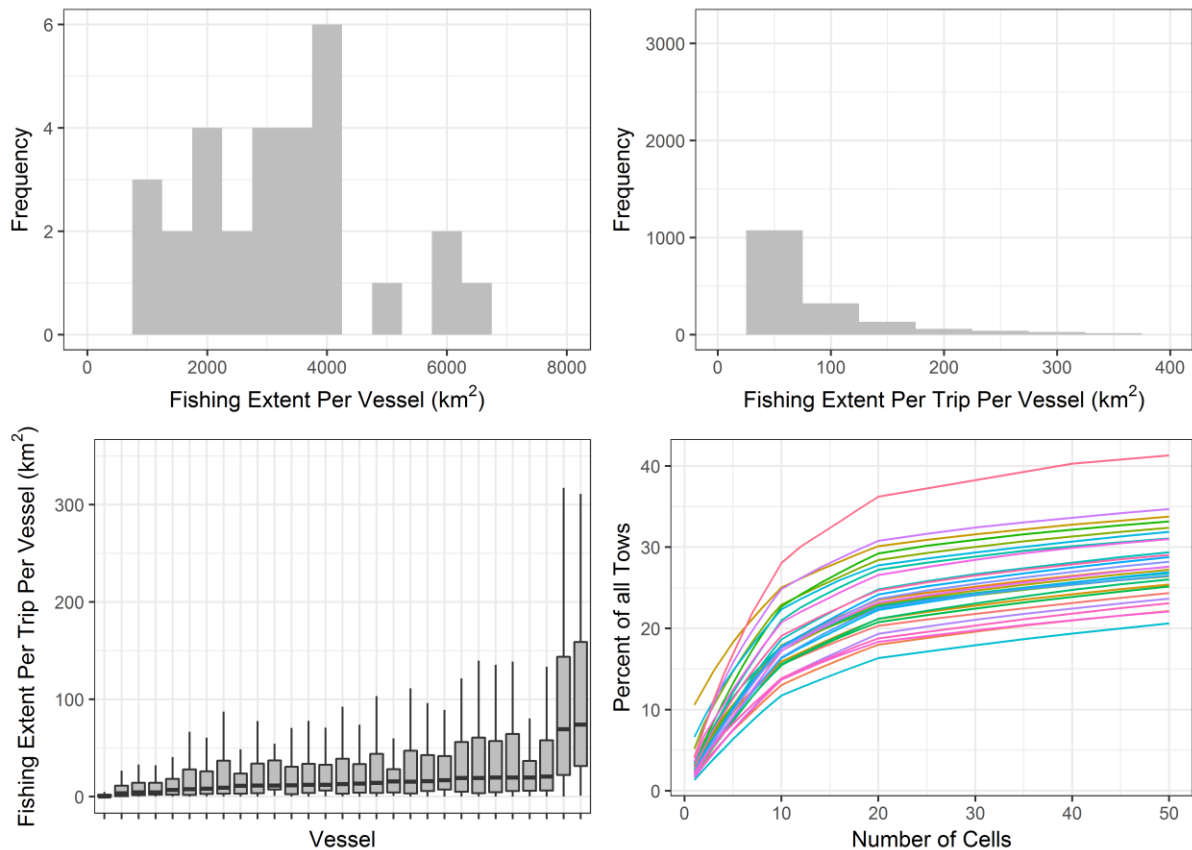
Figure 3.8. Individual variation in fishing extent and location. A) The total extent of all fishing points by each vessel. B) The extent of fishing points per trip. C) Individual variation in the extent of all fishing points per trip. C) The spatial distribution of individuals' fishing effort, indicating the proportion of fishing activity recorded in few cells.

There was individual heterogeneity in catch rates and catch efficiencies (Figure 3.9). The total catch ($F_{(1,67)}$ = 38.59, R=0.36, p=<0.001), total fuel used ($F_{(1,67)}$ = 86.98, R=0.56, p=<0.001), and average catch rate ($F_{(1,65)}$ = 60.09, R=0.47, p=<0.001) increased with VCU, but the VPUF did not show a correlation with vessel size ($F_{(1,65)}$ = 0.72, R=0.00, p=0.40). One large vessel made very few trips, and so was removed from the correlation analysis of catches as an outlier.
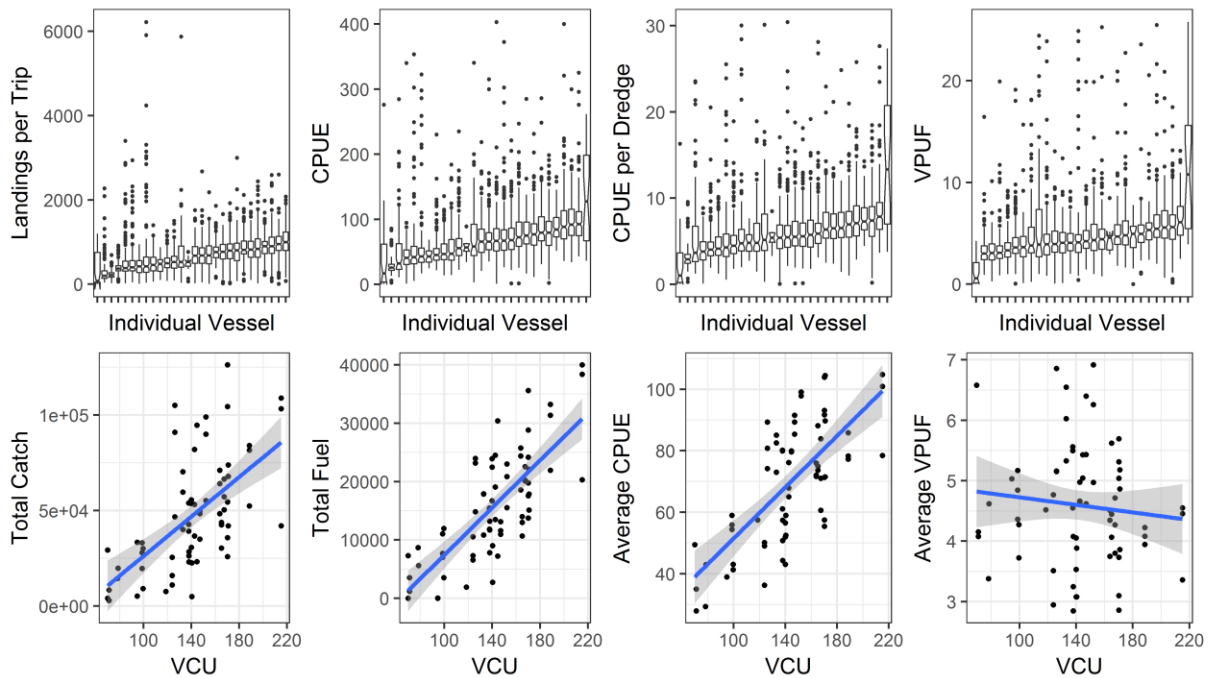
Figure 3.9. Individual variation in landings and catch rates (top row), and the relationship between catches and vessel size (bottom row). CPUE = catch per unit effort. VPUF = catch value per unit of fuel consumed

3.4.5. How do patterns in activity differ between Manx and external vessels?

Between 2011 – 2013 fishing trips were made by 29 individual Manx vessels, and 106 individual External vessels. External vessels (i.e. non-Manx vessels) were comprised of English, Scottish, Welsh, Northern Irish, Irish and Belgian vessels, who accounted for over half of the recorded trips over the study season (5969 logbook records, cf. 4903 by Manx vessels). Of these, 59% of the logbook records were from Scottish, 25% from Northern Irish, 15% from English, and <1% each from Welsh, Belgian and Irish vessels. External vessels accounted for the largest proportion of recorded landings over the study season (6600 tonnes of king scallops cf. 3500 tonnes by Manx vessels).

External vessels fished in 56% of the territorial sea in 2011, 2012, and in 2013, similar to the 48%, 54% and 56% of the territorial Sea fished by Manx vessels in 2011, 2012, and 2013 respectively (Figure 3.10). External vessels made 42% of their trips to CHI, 41% to EDG, 6 % to POA and 11% to TAR. Manx vessels made 36% of their trips to CHI, 36% to EDG, < 1% to POA and 27% to TAR. Manx vessels therefore showed more of a preference towards TAR than external vessels, and external vessels showed more of a preference towards POA more than Manx vessels. POA is located to the north of the island, therefore the ground of closest proximity to Scottish ports.
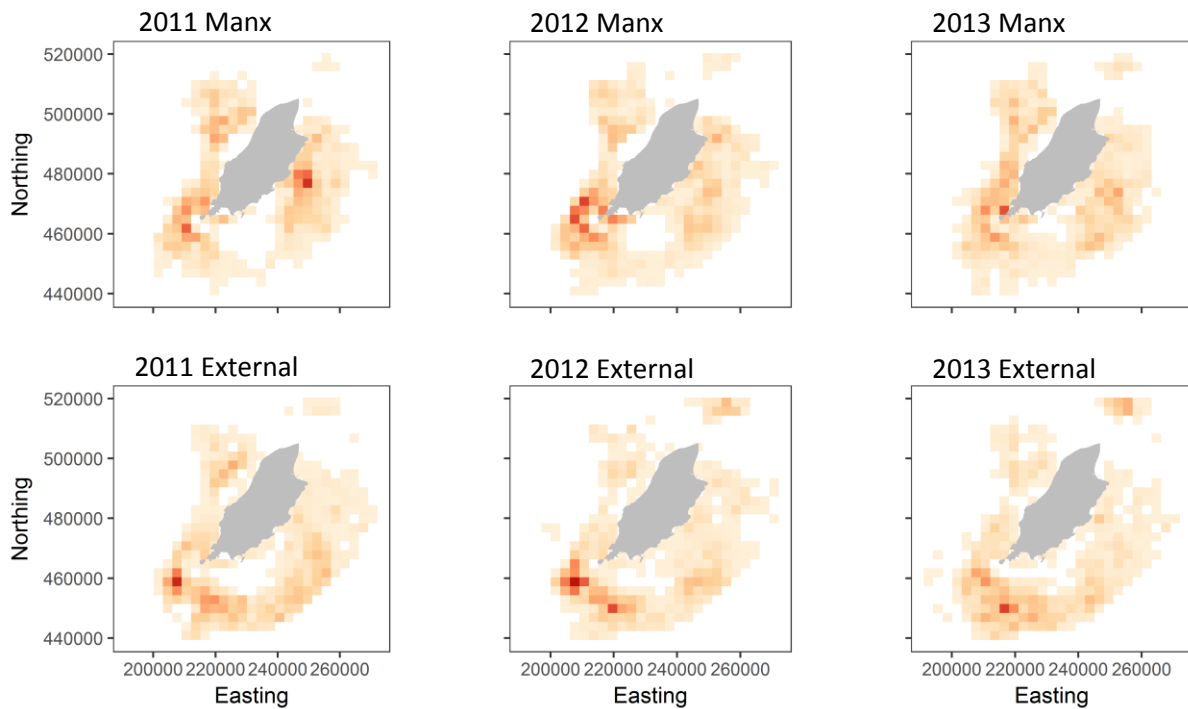
Figure 3.10. Fishing footprint by Manx vessels (top row) and external vessels (bottom row) in 2011 – 2013 (left – right).

The number of trips made by external vessels was correlated with the number of trips made by Manx vessels (Figure 3.11, Pearson correlation, r = 0.58, n = 19, p = 0.01). The correlation was stronger in the first five months of the fishing season (Pearson correlation, r = 0.77, n = 13, p < 0.001); in the last two months of the fishing season, external vessels made fewer trips than Manx vessels. The wave heights experienced by vessels from each nationality were similar, suggesting that vessels fished under similar daily conditions, although the Belgian vessels appeared to make their trips mainly during rougher months, which could relate to the start of the fishing season when catches were perhaps higher (Figure 3.11).
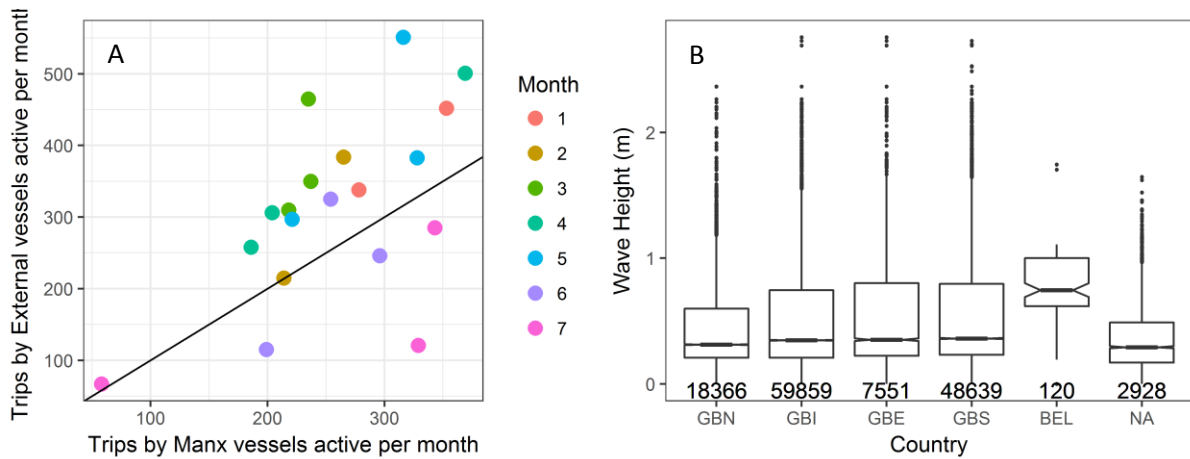
Figure 3.11. A) The number of trips made by Manx and by External vessels per month (2011-2013 therefore multiple points per month), and B) the wave heights experienced during fishing trips according to the nationality of the vessel. The numbers under the boxplots indicate the number of data points.

External vessels landed slightly higher quantities of scallops per trip, but achieved a similar CPUE (Figure 3.12). External vessels were larger than Manx vessels, and made more trips that were longer in duration. Some trips by external vessels showed a lower CPUE and VPUF than Manx vessels, with Manx trips slightly more skewed to higher VPUF. Nonetheless, there were not substantial differences between the catches of Manx and External vessels (Table 3.7; Figure 3.12).
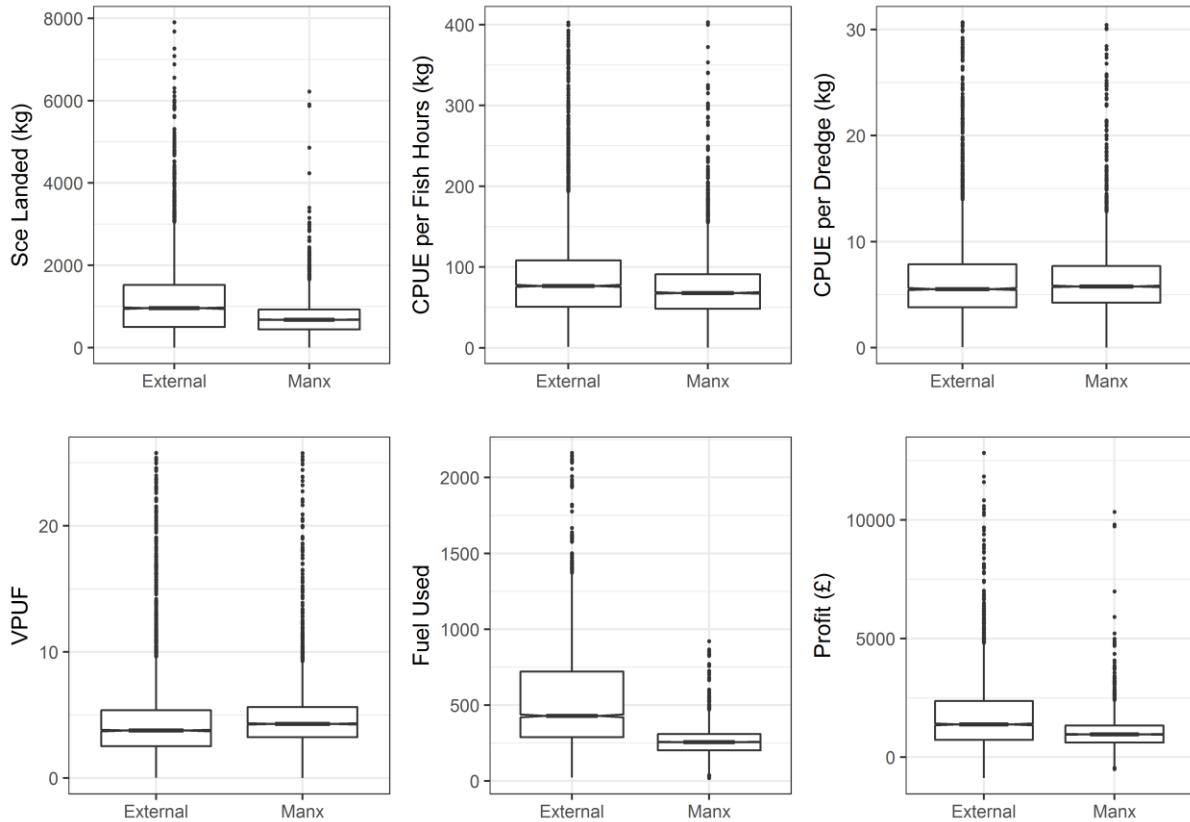
Figure 3.12. Boxplots of average landings characteristics per vessel over a scallop fishing season, comparing Manx and External vessels.

Table 3.7: Characteristics of the logbook trips recorded during the study period.

	Manx			External		
	Mean	Min	Max	Mean	Min	Max
Registered Length (m)	14.17	9.84	18.25	17.37	9.45	40.11
Engine Power	164.8	60.0	372.0	270.4	66.0	1095.0
Gross tonnage	33.48	1.22	85.00	68.58	4.70	396.00
Fuel use per trip	260.80	18.77	921.5	538.40	21.41	2163.0
CPUE (kg per dredge hour)	6.38	0.017	30.42	6.31	0.06	30.67
VPUF (Value per unit fuel)	4.77	0.00	25.76	4.51	0.03	25.49

3.5. Discussion

When attempting to build an individual-based model that can predict the behavioural response of fishermen to management, a detailed understanding is required of the characteristics of, and behaviours in, the system to be modelled. This Chapter provided a characterisation of fishing activity in the Isle of Man scallop fishery, which informed the development of an IBM. In addition, it documented values and patterns in the system (e.g. catches, costs, spatial distribution of effort) that could be used for model validation.

3.5.1. Informing Model Structure

VMS and logbook data highlighted characteristics of the Isle of Man scallop fishery relevant to developing an individual-based model of fishing behaviour. At its simplest level, identifying characteristic patterns in a system informs the structure of the model in terms of what entities and processes are required. For example, the Isle of Man scallop fishery is a simple system with a small number of vessels (26) operating mainly day trips, largely steaming from and returning to the same port, and completing the majority of fishing within the 12nm Sea. Fishing activity was concentrated over known grounds, more so at the start of the season, then the distribution widened as the season progressed. This could indicate targeting behaviour, with vessels prosecuting the areas with most scallops at the start of the season, and as these grounds become depleted, moving to less profitable areas as the season progressed (Charnov, 1976; Murray *et al.*, 2011). With vessels leaving from and returning to the same 'home port' this could suggest that a foraging model based on central place foraging (CPF) would be an appropriate representation of the system. CPF theory predicts foraging activity in systems where foragers must return to a 'home' location at the end of a foraging trip, taking account of the travel cost when deciding where to forage (Orians and Pearson, 1979). Such a model would therefore require processes to calculate the travel cost associated with fishing grounds, in relation to the expected catch rates.

The analysis highlighted considerable heterogeneity between individuals even in a small fishery. There was variability in individual fishers' abilities and requirements; some vessels caught more than others, and some were able to fish in higher sea states than others. When developing a model it would be necessary to decide what level of detail is required in the model, relating to the questions being asked; if a model was designed to predict how impacts of management may vary between fishers within in a fishery, it would be necessary to incorporate all of the variability in ability and requirements between individuals.

External vessels contributed a considerable proportion of the catch from the Isle of Man, therefore it would be necessary to include this extraction in any model of the fishery. The spatial distribution of effort by external vessels was slightly different to the distribution of Manx vessel effort, and the amount of effort in the later part of the season was less correlated to the Manx effort. External vessels may decide when and where to fish in a different way to the Manx vessels; in a model the behavioural mechanisms with which individuals decide when and where to fish may therefore need to be different. In particular, External vessels may be more likely, or more able, to fish in alternative locations (i.e. more fishing opportunities available to them, such as permissions in their home country or being larger and able to travel further afield), which in a model could translate as less effort by these externals vessels in Manx waters when catches are lower. In contrast, Manx vessels are perhaps less likely to leave the Manx fishery. Only six out of 16 fishers stated they had travelled further than 50 miles away from the Isle of Man for fishing; most of these fishers stated they had not done this often, identifying only a single year or extreme circumstance under which they left the Manx fishery. Seven out of 16 interviewed fishers stated they may sometimes fish for another species (mostly *Nephrops norvegicus*), but six of these stated they had only done this in one year. Therefore, the decision process of whether or not to fish each day may need to be a different for Manx and External vessels. External vessels (such as Scottish or Irish vessels) may be able to select between fishing in Manx waters, and their own waters, on a more day-to-day basis. The data presented in this Chapter were only recorded in and around the Isle of Man scallop fishery, therefore it was not possible to understand how often the External vessels fished in Manx waters compared to elsewhere.

3.5.2. Informing Behavioural Rules in a Model

There are some unrealistic assumptions associated with optimal foraging theory, these include: foragers have ideal knowledge of resource levels in each patch; foragers are able to move equally between all patches; and foragers have equal competitive abilities. There was spatial variation in catch rates between grounds and ports, which suggests some possible violations of these assumptions. There could be two reasons why fishers did not move to a ground with higher catch rates: fishers may not have ideal knowledge of all resource levels in patches, and therefore did not know that there were better catch rates to be achieved on a different ground (this is unlikely as there is considerable sharing of information among fishers in the Isle of Man as it is a small fishery); and/or fishers may be aware of the better catch rates but are unable or unwilling to change grounds.

Some vessels demonstrated strong location affinity, with a large proportion of their fishing activity occurring in a small area. Whilst this activity may have been focussed over highly profitable scallop grounds, it is also possible that this activity could have been due to ground preference. A reluctance to change grounds could be related to risk averse behaviour, with vessels demonstrating habitual preference for a particular ground, being averse to try new fishing locations due to safety considerations. Indeed, following area closures in the Isle of Man, some vessels remained fishing in seemingly low yield areas, stating that they were not able to fish areas on the other side of the island (Karen McHarg, Director of Fisheries, DEFA, pers. comms.). This suggests that modelling fishers with truly optimal behaviour may overestimate catches. This is in congruence with literature that suggests that fishers are not always profit maximisers (Holland, 2008), and that they are risk averse and often show strong patch affinity and inertia to change (Eggert, 2007).

Interference competition can influence the distribution of foragers (Hassell and Varley, 1969), and has also been demonstrated in fisheries (Poos and Rijnsdorp, 2007; Rijnsdorp, 2000). Nevertheless, in the Isle of Man fishers stated that proximity to other vessels was unimportant, with 11 out of 16 vessels stating the closest they would fish to another vessel was 0nm, and the others stating values less than 0.5nm. Some fishers explained that as all vessels tow the gear around the grounds in the same direction, it is possible to be very close to other vessels. Therefore, in a model of scallop fisher foraging behaviour, displacement competition may not be relevant.

Wind direction and sea state appeared to influence the spatial distribution of activity, with vessel activity clustered on the opposite side of the island to the strong prevailing winds in November and December. Nevertheless, as trips from each port tended to be to the grounds closest to that port, the weather conditions may have had more of an influence on the decision of whether to fish or not per day, rather than directly influencing where they fish on a particular day. Fishers stated that an average of 111 days per year are lost to bad weather (median of 90, range from 35 – 210) (Chapter 2). This value related to both the queen scallop and king scallop fishing season, but as the king scallop fishing season takes place over winter months (Nov – May), it is more likely that a higher proportion of these days related to the king season. Using a mean wave height per ground suggested that 6 – 19 days per king scallop season could be lost to bad weather (wave height > 2.45m threshold identified in the surveys), whereas using a maximum wave height per ground suggested 39 – 55 days could be lost to bad weather. Fishers may therefore have overestimated the frequency with which sea state is a limiting factor, or, using a modelled average or maximum wave height at a broad ground area may underestimate the number of days a vessel is unable to fish. However, external environmental variables may not be the only influencing factor on whether vessels fish; as demonstrated here, even with 0m wave height there is on average a 40% chance of fishing. The

previous day's catch also influenced the likelihood of fishing; as catches fell, the chance of fishing again the following day also fell. As the season progressed, the likelihood of fishing also reduced. There was considerable variation between individuals in their likelihood of fishing under different conditions.

3.5.3. Predicting the outcome of management

Vessels demonstrated behaviour that has been termed 'fishing the line', in which activity was concentrated around the edge of closed areas (Goñi *et al.*, 2008). A model may need to account for this response if predicting the effect of closed areas; nevertheless, the requirement to include this response would depend on the scale of the model, and the level at which the model was validated. In addition, if the spill-over effect is merely perceived (i.e. there is not a real increase in catches, but fishers perceive there is and thus increase effort), or if the stock dynamics and thus spill-over are not modelled, the 'fishing the line' response would have to be achieved through model calibration by imposing a rule of thumb.

In EBFM or SBFM, the wider ecosystem impacts of a management action should be considered (Pikitch *et al.*, 2004). If management simply displaces effort to another less fished, more sensitive habitat, there may not be a positive environmental impact (Dinmore *et al.*, 2003). If effort is displaced to another fishery with less stringent management, the problem of overfishing may just be relocated. In this context, it is necessary to consider the exit decisions of fishers. There can be a range of variables influencing the decision of a vessel to leave a fishery, and they may vary between individuals (Bucaram and Hearn, 2014). Whilst Manx vessels may be unlikely to leave the Isle of Man to fish elsewhere, non-Manx vessels may be more likely to do this. The number of trips made per month by Manx and external vessels was correlated, but less so in the last two months of the season. This may have been related to catches, i.e. External vessels may withdraw from the fishery when catches get low, but Manx vessels remain in the fishery. When asked how easy it would be to find an alternative source of income if they were not fishing for scallops, eight said it would be difficult, two said impossible, only three said easy, and the remaining were unsure. This indicates that it is possible that Manx fishers may turn to other fisheries or other sources of income, but it is more associated with extreme conditions.

If management causes a decline in catches or profitability, External vessels may be less likely to fish in the Isle of Man, displacing their effort to another fishery. Conversely, when scallop catches are high, more external vessels may join the fishery (BBC, 2016). Whilst outside the scope of this project,

predicting the wider response of vessels (particularly non-Manx vessels) may be an important component of an EBAFM on a larger scale (i.e. with displacement between fisheries). Manx fishers have suggested, both in the questionnaire survey (6 out of 16) and in subsequent media interviews (BBC, 2016), that excluding External larger vessels could benefit the fishery. Catches by External vessels constituted a substantial proportion of the landings, therefore it would likely be beneficial to the Manx fleet to exclude this effort; but this effort would be displaced to another area or another fishery. This highlights how there can be multiple drivers, and different groups can have different scales for the definition of sustainably managed (Hilborn *et al.*, 2015); the Manx fishery itself may be more sustainable if External vessels were excluded, but the displaced effort may cause environmental damage or overfishing elsewhere.

3.5.4. Informing model validation

This analysis identified characteristic patterns (e.g. in catches, in the spatial distribution of effort) in the Isle of Man scallop fishery, which could be used to validate an IBM of fishing activity. Both strong and weak patterns should be considered (Grimm and Railsback, 2012); strong patterns are often described by data or equations, whereas weak patterns are often more qualitative. A strong pattern is something pronounced, for example in a fishery this might be spatial patterns in effort; recreating this could be a good indicator that you have captured the system well. Nevertheless, weak patterns (e.g. vessels preferring one ground over another) are less pronounced, and may be reproducible by different mechanisms in a model. If a model can reproduce multiple weak patterns it can be a strong indicator that structural realism has been achieved (Grimm and Railsback, 2012). The spatial pattern of effort is a strong pattern that characterises the Isle of Man system; activity is clustered over known fishing grounds, and the extent increases as the season progresses. In addition, there were multiple other weaker patterns that could be used to validate a model. For example, there were different proportions to trips to each fishing ground, and the proportion of the catch from each ground was not the same as the proportion of effort at each ground (i.e. the ground with the most effort was not the ground with the highest landings). There was individual variation in catches, and catches and costs varied with vessel size. Different processes in the model will influence these patterns, so recreating multiple patterns gives more confidence that the underlying mechanisms of behaviour have been realistically captured (Grimm and Railsback, 2012).

3.6. Conclusion

This analysis demonstrated that VMS and logbook data can be used to characterise activity in a fishing system, providing the information required to inform model development, and the values and patterns required to validate such a model. In addition, questionnaire interview data provided useful contextual information to consider alongside these trends. Developing an IBM of fishing activity can have relatively substantial data requirements, but this analysis has demonstrated that in systems with vessel monitoring system and logbook recording in place, existing data could provide much of the information required to develop such a model.

3.7. Acknowledgements

3.8. References

Bates, D., Maechler, M., Bolker, B., and Walker, S. 2015. Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software, 67: 1–48.

BBC. 2016. Boat race over `unusually good` Isle of Man king scallop crop. BBC. http://www.bbc.co.uk/news/world-europe-isle-of-man-37911565.

Begossi, A. 1992. The use of optimal foraging theory in the understanding of fishing strategies: A case from Sepetiba Bay (Rio de Janeiro State, Brazil). Human Ecology, 20: 463–475.

Begossi, A., Clauzet, M., Hanazaki, N., Lopes, P. F., and Ramires, M. 2009. Fishers' decision making, optimal foraging and management. *In* III Seminario de Gestao Socioambiental para o Desenvolvimento Sustentavel da Aquicultura e da Pesca no Brasil - III SEGAP 2009, pp. 1–5.

Bucaram, S. J., and Hearn, A. 2014. Factors that influence the entry–exit decision and intensity of participation of fishing fleet for the Galapagos lobster fishery. Marine Policy, 43: 80–88. Elsevier.

Burgess, M., Drexler, M., Axtell, R., Bailey, R., Watson, J., Ananthanaryanan, A., Cabral, R., *et al.* 2017. The role of agent-based modeling in systems-based fishery management. Fish and Fisheries (In Review).

Charnov, E. L. 1976. Optimal Foraging, the Marginal Value Theorem. Theoretical Population Ecology, 9: 129–136.

de Oliveira, L. E. C., and Begossi, A. 2011. Last Trip Return Rate Influence Patch Choice Decisions of Small-Scale Shrimp Trawlers: Optimal Foraging in São Francisco, Coastal Brazil. Human Ecology, 39: 323–332.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES Journal of Marine Science, 60: 371–380.

Eggert, H. 2007. Small-scale Fishermen and Risk Preferences. Marine Resource Economics, 22: 49 - 67.

Fulton, E. a, Smith, A. D. M., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Goñi, R., Adlerstein, S., Alvarez-Berastegui, D., Forcada, A., Reñones, O., Criquet, G., Polti, S., *et al.* 2008. Spillover from six western Mediterranean marine protected areas: evidence from

artisanal fisheries. Marine Ecology Progress Series, 366: 159–174.

Goss-custard, J. D., Road, C., and Stillman, R. A. 2008. Individual-based models and the management of shorebird populations. Natural Resource Modeling, 21: 3–71.

Grimm, V., Frank, K., Jeltsch, F., Brandl, R., Uchmański, J., and Wissel, C. 1996. Pattern-oriented modelling in population ecology. Science of The Total Environment, 183: 151–166.

Grimm, V., and Railsback, S. F. 2012. Pattern-oriented modelling: a 'multi-scope' for predictive systems ecology. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 298–310. The Royal Society.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H. H., *et al.* 2005. Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. Science, 310: 987-991.

Gruffydd, L. L. D. 1972. Mortality of scallops on a Manx scallop bed due to fishing. Journal of Marine Biological Association, 52: 449–455.

Hanley, L., Read, A., McHarg, K., Eastwood, C., Hamilton, A., Milsom, N., Eaton, J., *et al.* 2013. Commercial Fisheries and Sea Angling. *In* Manx Marine Environmental Assessment. Isle of Man Plan. Isle of Man Government., p. 64. Ed. by Hanley et al.

Hassell, M. P., and Varley, G. C. 1969. New inductive population model for insect parasites and its bearing on biological control. Nature, 223: 1133–1137.

Hilborn, R. 2007. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Hilborn, R., Fulton, E. A., Green, B. S., Hartmann, K., Tracey, S. R., and Watson, R. A. 2015. When is a fishery sustainable ? Canadian Journal of Fisheries and Aquatic Sciences, 1441: 1–46.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., *et al.* 2004. When can marine reserves improve fisheries management? Ocean & Coastal Management, 47: 197–205.

Hintzen, N. T., Bastardie, F., Beare, D., Piet, G. J., Ulrich, C., Deporte, N., Egekvist, J., *et al.* 2012. VMStools: Open-source software for the processing, analysis and visualisation of fisheries logbook and VMS data. Fisheries Research, 115–116: 31–43.

Holland, D. 2008. Are Fishermen Rational? A Fishing Expedition. Marine Resource Economics, 23: 325–344.

Jenkins, S., and Brand, A.R. 2001 The effect of dredge capture on the escape response of the great scallop, *Pecten maximus* (L.): implications for the survival of undersized discards. Journal of Experimental Marine Biology and Ecology, 266: 33 - 50.

Lambert, G. I., Jennings, S., Hiddink, J. G., Hintzen, N. T., Hinz, H., Kaiser, M. J., and Murray, L. G. 2012. Implications of using alternative methods of vessel monitoring system (VMS) data analysis to describe fishing activities and impacts. ICES Journal of Marine Science, 69: 682–693.

Lee, J., South, a. B., and Jennings, S. 2010. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES Journal of Marine Science, 67: 1260–1271.

Lee, A. Van Der, Gillis, D. M., and Comeau, P. 2014. Comparative analysis of the spatial distribution of fishing effort contrasting ecological isodars and discrete choice models. Canadian Journal of Fisheries and Aquatic Sciences, 71: 141–150.

MacArthur, R. H., and Pianka, E. R. 1966. On Optimal Use of a Patchy Environment. The American Naturalist, 100: 603–609.

Murray, L. G., Hinz, H., Hold, N., and Kaiser, M. J. 2013. The effectiveness of using CPUE data derived from Vessel Monitoring Systems and fisheries logbooks to estimate scallop biomass. ICES Journal of Marine Science, 70: 1330–1340.

Murray, L., Hinz, H., and Kaiser, M. 2011. Functional response of fishers in the Isle of Man scallop fishery. Marine Ecology Progress Series, 430: 157–169.

Orians, G. H., and Pearson, E. 1979. On the Theory of Central Place Foraging. *In* Analysis of Ecological Systems. Ed. by D. J. Honrs, G. R. Stairs, and R. D. Mitchell. Ohio State University, Columbus.

Pascoe, S., and Mardle, S. 2005. Anticipating fisher response to management: Can economics help? ICES Annual Science Conference. Aberdeen.

Pikitch, E. K., Santora, C., Babcock, E. A., Bakun, A., Bonfil, R., Conover, D. O., Dayton, P., *et al.* 2004. Ecosystem-Based Fishery Management. Science, 305: 346 LP-347.

Poos, J., and Rijnsdorp, A. D. 2007. An ' experiment ' on effort allocation of fishing vessels : the role of interference competition and area specialization. Canadian Journal of Fisheries and Aquatic Sciences, 64: 304–313.

Railsback, S. F., and Johnson, M. D. 2011. Pattern-oriented modelling of bird foraging and pest control in coffee farms. Ecological Modelling, 222: 3305–3319.

Rijnsdorp, a. 2000. Competitive interactions among beam trawlers exploiting local patches of flatfish in the North Sea. ICES Journal of Marine Science, 57: 894–902.

Shepperson, J., Murray, L. G., Mackinson, S., Bell, E., and Kaiser, M. J. 2016. Use of a choice-based survey approach to characterise fishing behaviour in a scallop fishery. Environmental Modelling & Software, 86: 116–130.

Sosis, R. 2002. Patch Choice Decisions among Ifaluk Fishers. American Anthropologist, 104: 583–598.

Stillman, R. a. 2008. MORPH—An individual-based model to predict the effect of environmental change on foraging animal populations. Ecological Modelling, 216: 265–276.

Stillman, R. A., Railsback, S. F., Giske, J., Berger, U., and Grimm, V. 2015. Making predictions in a changing world: The benefits of individual-based ecology. BioScience, 65: 140–150.

Zuur, A. ., Ieno, E. N., Walker, N., Saveliev, A. A., and Smith, G. M. 2009. Mixed effects models and extensions in ecology with R. Springer, New York.

CHAPTER 4: A Comparison of VMS and AIS Data; the Effect of Vessel Position Recording Frequency and Aggregation on Estimates of Fishing Footprints

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4.1. Abstract

Understanding the distribution of fishing activity is fundamental to quantifying its impact on the seabed. Vessel monitoring system (VMS) data provides a means to understand the footprint of scallop dredging and other fisheries. Automatic Information System (AIS) data could offer a higher resolution alternative to VMS data, but before AIS data can be used as a data source for management, differences in coverage and interpretation must be understood and addressed.

Concurrent, individually identifiable, VMS and AIS data for vessels in the English Channel scallop fishery were compared. There were substantial gaps in the AIS data coverage, the magnitude of which varied between individual vessels; 45 – 99% of each individual vessel's VMS data had no directly matching AIS data. Using only directly matching AIS data, VMS data overestimated the fishing effort by 129 hours compared to the directly matching AIS data. The method of analysis also influenced the interpretation of the footprint and extent, for example, analysing VMS data with a 1km grid underestimated fishing extent, but a 5km grid overestimated extent. Interpolating the VMS data improved the footprint estimate.

The present gaps in coverage of AIS data may make it inappropriate for absolute estimates of fishing footprints and intensity. VMS already provides a means of collecting more complete fishing position data, shielded from public view. Hence, there is a clear incentive to increase poll frequency to provide the basis for more accurate calculation of fishing footprints, which would ultimately benefit both fishers and scientists.

4.2. Introduction

4.2.1. We need to understand fishing footprints to understand fishing impacts

Physical disturbance by towed bottom-fishing gears is the largest cause of human disturbance to continental shelves in all areas of the world. In order to understand the extent and consequences of these disturbances it is necessary to have an accurate understanding of the distribution in space and time of that disturbance. For these reasons, the use of vessel tracking data to analyse patterns of fishing effort and the impact of fishing pressure on marine environments is a key area of fisheries science (Campbell *et al.*, 2014; Hintzen *et al.*, 2012; Joo *et al.*, 2015; Lee *et al.*, 2010; Mccauley *et al.*, 2016; Russo *et al.*, 2016).

4.2.2. VMS data is increasingly used to analyse fishing activity, but has limitations

Vessel Monitoring Systems (VMS) were introduced as an enforcement tool, but the resulting data are increasingly important for scientific research and management (Lambert *et al.*, 2012; Murray *et al.*, 2011, 2013). Despite the importance of these data, the temporal resolution of VMS is relatively low in Europe, usually with a 2 hourly poll rate. The poll rate can be varied by a fisheries management authority in accordance with the intensity of a fisheries management regime and the resources available to respond to VMS observations (FAO, 1998). The 2 hourly poll rate in Europe is designed as a compromise between adequate resolution and costs to fishers. Interpolation of VMS data is typically used to fill in the gaps between successive VMS points to produce a continuous track. VMS data can be joined to grids to analyse the extent of, and patterns in fishing intensity, either as raw point data, or as interpolated tracks. However, the methodology used to analyse VMS data can influence the estimation of fishing intensity (Piet and Hintzen, 2012), and the relationship between fishing intensity and epifaunal biomass (Lambert *et al.*, 2012). In particular, the grid cell size used for analysis influences the intensity estimates (Dinmore *et al.*, 2003; Hinz *et al.*, 2013; Lambert *et al.*, 2012; Piet and Quirijns, 2009).

4.2.3. AIS data has a higher temporal resolution, and could be used to investigate fishing activity.

There has been a recent increase in interest in the potential for using publicly available Automatic Identification System (AIS) vessel tracking data to investigate fishing activity (Mccauley *et al.*, 2016; Natale *et al.*, 2015; Russo *et al.*, 2016). AIS data is openly available to the public, at high resolution, whilst VMS data is subject to strict confidentiality regulations, which mean often only highly aggregated data is available to scientists (Hinz et al., 2013). Whilst VMS is mandatory on fishing vessels >12m in length in the European Union for enforcement purposes (EC, 2009), AIS is required on vessels >15m for safety purposes. Nevertheless, aspects of the AIS technology and legislation, mean fishing activity may not be completely recorded by AIS (McCauley et al., 2016). Thus, whilst access to VMS data is subject to confidentiality issues that degrades its utility for research purposes (Hinz *et al.*, 2013), AIS data has different disadvantages, as it can lack consistent coverage. AIS signals are recorded in a different way to VMS data, in that they are broadcast omni-directionally and can be picked up by receivers on land, or by other vessels, as the system was designed to reduce collisions and offer safety mainly when near other traffic or near ports (Russo *et al.*, 2016). If a vessel is out of reach of a land based station, the signal must be transmitted from vessel to vessel until it reaches a land station. In areas with relatively low vessel densities, this could cause gaps in coverage. Signals can also be 'lost' in areas of very high density traffic. In addition, skippers can turn down the power on the AIS, which reduces the range of the signal, further increasing the likelihood of gaps in coverage. McCauley et al., (2016) argue that having an AIS system on board a vessel, but failing to use it properly, should no longer be viewed as legal compliance. It is also possible for skippers to falsify AIS data, and provide incorrect vessel IDs (McCauley et al., 2016), with the vessel identity of AIS signals not subjected to the same validation process by inspection agencies as VMS data. Despite the positional accuracy of AIS data being comparable to VMS data, there can be considerable variation in spatial coverage between different fleets of vessels (Russo *et al.*, 2016).

4.2.4. High resolution AIS data might improve footprint estimates of scallop dredging

Besides the lower overall fleet coverage of AIS data (i.e. number of vessels with AIS), it would be useful to understand more about the differences in inferred fishing activity between VMS and AIS data, where the coverage is concurrent. There can be considerable gaps in AIS data coverage in

space and time within fleets (Natale *et al.*, 2015; Russo *et al.*, 2016), but there has not yet been a comparison of the recorded activity by the two data sources specifically on trips where both VMS and AIS were actively transmitting data. In situations where AIS is the primary data source available to scientists, e.g. in areas where only highly aggregated VMS data is available, it is important to know how the conclusions drawn from AIS would correlate with those drawn from VMS data. In addition, an analysis of concurrent VMS and AIS data would enable us to understand better the complexity in patterns of fishing that may be missed by VMS data due to the issue of temporal position frequency. The structure of the VMS and AIS data itself is essentially the same, a file with coordinates, speed, heading, and vessel ID, which means the same data processing techniques can simply be applied. Nevertheless, despite using the same processing techniques, there could be differences in the resulting conclusions due to differences in the way the data were generated. Primarily, AIS data is available at a much higher poll frequency than VMS data. Finer scale patterns in activity may therefore be seen with AIS data, for example, using a longer 2 hourly poll frequency in VMS could miss shorter steaming sections between tows, giving the impression of long continuous fishing activity, potentially over estimating fishing activity. Alternatively, due to the difficulty in accurately interpolating the tracks between 2 hourly position records, the VMS could also lead to an under-estimate of the footprint of fishing.

Understanding this error becomes particularly important when attempting to understand the environmental footprint of different fishing activities. In this paper, the focus is on scallop fishing, which is considered one of the least environmentally compatible forms of towed bottom fishing (Kaiser et al. 2006). European Union Directives such as the Marine Strategy Framework Directive (MFSD) and Good Ecological Status (GES) use the fishing footprint (spatial distribution of fishing activity) as an indicator of ecosystem health. Understanding the distribution of fishing activity is fundamental to understanding and quantifying the impact that fishing has on the seabed (Kaiser et al., 2016). VMS data provides a means to understand the footprint of scallop dredging and other fisheries and this has become a research field of its own (Lambert et al., 2012; Hinz et al., 2013; Eigaard et al., 2016). However, there is a conflict between the requirement for high temporal and spatial resolution data needed for scientific research, and the publicly available lower temporal and spatial resolution data to uphold confidentiality of commercially sensitive data (Hinz et al., 2012, Lambert et al., 2012). Vessels such as trawlers often tow fishing gear for in excess of four hours and often in a single direction with few deviations. In contrast, scallop dredgers can make short tows (~20 minutes), make tight turns and often tow parallel to their previous tracks, which can make the prediction of trajectories using interpolation methods difficult when the resolution of data is low (Lambert et al., 2012). With scallop dredging activity, higher resolution AIS data may therefore be

better able to capture (1) the true fishing footprint by better capturing the sharp turns made by vessels; and (2) the true fishing effort level, by better capturing the time spent in each activity state (i.e. fishing cf. steaming). This could provide insights into the appropriate treatment of lower resolution VMS data.

Nevertheless, this benefit of higher poll frequency in AIS data may be counteracted by gaps in coverage. Before AIS data can be used as a data source for management, these differences in coverage and interpretation must be understood and addressed. This paper seeks to address this gap in understanding, by comparing the fishing activity of scallop vessels in the English Channel Scallop fishery, on days for which it was possible to obtain both VMS and AIS position records.

4.2.5. Aims

The main aims of this paper were to: (1) determine the relative coverage of AIS data in relation to VMS data at both the fleet and an individual vessel level; and (2) for comparable data (from the same vessels in the same time period), determine whether the fishing extent and intensity predicted by three common methods of VMS data analysis (point density, straight line interpolation (Stelzenmuller et al. 2008), and cubic Hermite spline interpolation (Hintzen et al. 2010)) showed a comparable accuracy to the higher poll frequency AIS data. Finally, conclusions were drawn about the influence of data accuracy on estimates of fishing footprints using these two different data sources, particularly relating to the level of aggregation at which data is analysed.

4.3. Methods

4.3.1. Data Coverage
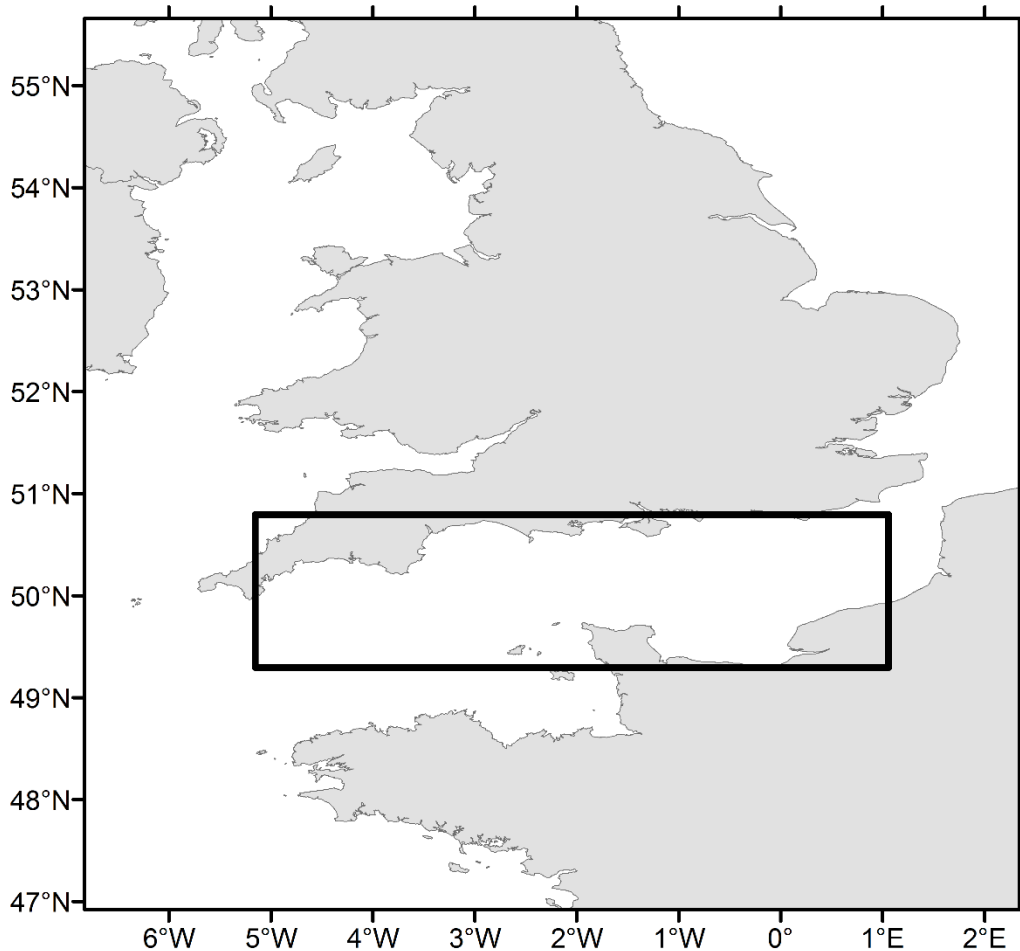
Figure 4.1. The spatial window in which the VMS and AIS records were recorded. The actual positions of data points are concealed for confidentiality.

VMS and AIS data were obtained for vessels in the English Channel scallop fishery, in the calendar year 2012, in the spatial window shown in Figure 4.1. Eight scallop dredgers (all >15 m L.O.A.) in the English Channel gave permission for their raw VMS data to be used in this analysis. The VMS data included vessel identification data, position, time and speed. AIS position, time, speed, and vessel identification data for the same eight vessels over the same time period were obtained from the company AstraPaging Ltd (http://www.astrapaging.com/), a private AIS data provider. The Maritime Mobile Service Identity (MMSI) field, a nine digit number uniquely identifying a ship radio station

installed on each vessel, was used to link the VMS and AIS between vessels. VMS data was provided at a poll frequency of approximately 2 hours, and the AIS data was provided at a poll frequency of approximately 5 minutes.

AIS coverage can vary between fleets (Natale et al., 2015), and has also been shown to capture a smaller amount of fishing activity than VMS data (Russo et al., 2016). The main aim of the present study was to analyse fishing activity between directly comparable VMS and AIS data records from individual vessels, to compare the extent and intensity of fishing that was not confounded by varying data coverage (i.e. using data for the same vessels over the same time period). Therefore, following the initial assessment of data coverage, data that could not be matched were excluded from further analysis. For each date, a vessel's VMS data were removed from the analysis if that same vessel had not also recorded AIS data on that date, and vice versa; therefore the term 'comparable date' is used to signify a date on which a particular vessel had recorded both VMS and AIS, which generated 'comparable data'. Nevertheless, even if there were some VMS and AIS data for a vessel on a particular day/trip, either data set may not be complete within the trip. Thus a further category of matching data was identified, by extracting trips where the ratio of the duration of VMS:AIS points was between 0.8 and 1.2, i.e. there was less than 20% mismatch in the duration of VMS compared to AIS, so substantial sections of either data were not missing within a trip. There were therefore 2 categories of data: comparable data, which refers to trips for which there is some VMS and AIS for that vessel, but within trip completeness has not been quantified; and matching data, which refers to trips for which the ratio of VMS:AIS is between 0.8 – 1.2, meaning that there is more complete data within the trip. Only comparable or matching data were used in the comparisons of fishing activity, extent, intensity and track interpolation.

4.3.2. Data Processing

Both VMS and AIS datasets were subjected to the same data cleaning and processing strategy, using the *VMStools* packages in R (Hintzen *et al.*, 2012). Duplicate VMS records and records close to (within 1km of) port were removed, along with erroneous position records allocated to land (Lee *et al.*, 2010). Following examination of the frequency distribution of the recorded speeds, position records between 1 – 5knots were classed as fishing activity (Figure 4.2). The level of data retention of VMS and AIS data was recorded at each stage of data cleaning and processing, to identify differences and similarities in the data, and identify any substantial loss of data.
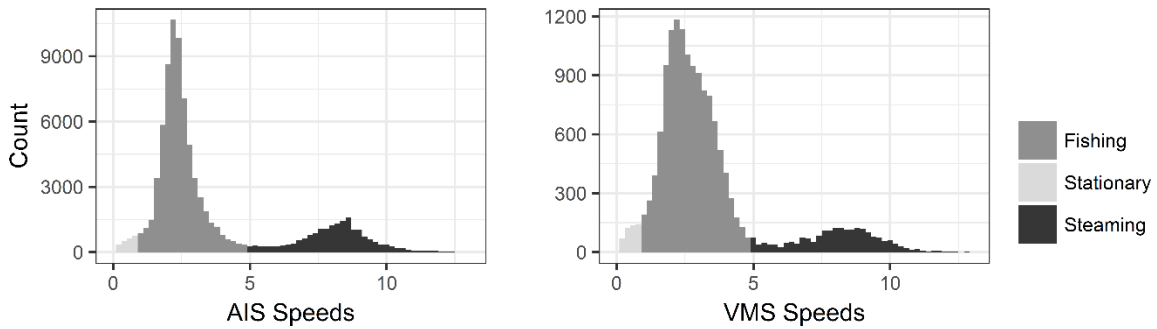
Figure 4.2. Speed frequency distribution, recorded by AIS and VMS data points

4.3.3. Interpolation of tracks

VMS and AIS data can be analysed in the raw point data format, or vessel tracks can be reconstructed using a straight line (SL) interpolation, or a cubic Hermite spline (cHs) interpolation (Hintzen et al., 2012). Succinctly, the cHs method uses information on vessel position, heading and speed at times t and t+1 to define a trajectory. The combination of speed and heading are represented by vectors, and vector length is multiplied by a parameter *fm* that influences the curvature of the interpolations (Lambert et al., 2012). The VMStools package in R provides a function for *fm* parameter optimisation; the high resolution AIS data was used to determine the optimal *fm* parameter for cHs interpolation of the VMS data. CHs interpolation of the AIS data was not possible, as there was no higher resolution data for the optimisation process, nevertheless the AIS points were at a high 5 minute poll frequency, so a SL interpolation would give a sufficient level of spatial detail in the tracks. The SL interpolation of the AIS data can be assumed as the most robust estimate of the path taken by the vessels due to its high poll frequency.

4.3.4. Data Analysis

The number and proportion of points classed as fishing activity were compared between data types and vessels, to identify differences between the data types, and whether these differences varied between individual vessels. To investigate the spatial extent of fishing activity, points that were classed as fishing activity were joined to spatial grids of 1km, 3km, 5km, and 10km in cell size. These grids were used to calculate the fishing extent and intensity. The interpolated tracks were turned into a series of points approximately every 30 seconds along the track, to analyse in the same way as the raw point data.

The extent of fishing was calculated by summing grid cells which had at least 1 fishing point in them, using each data type and interpolation method. This provides a simplified calculation of fishing extent, counting a grid cell as 'fished' completely if there are any fishing points present. The intensity of fishing was also calculated, as the swept area ratio, derived from the actual area swept within a grid cell (i.e. accounting for the fact that having a fishing point within a cell does not necessarily mean the whole grid cell is fished over). The area swept in each grid cell was calculated by summing the area swept per point in the cell, using each data type and interpolation method. Area swept per point was calculated as:

$$\text{Area swept (km}^2\text{)} = \text{speed (km/h)} * \text{time fishing (h)} * \text{total dredge width (km)}$$

where the total dredge width is assumed to be 0.018km for all vessels, corresponding to the width of 24 individual dredges each measuring 0.75m across. A fixed dredge width was assumed as the analysis is purely indicative, and the actual dredge width was unknown.

The swept area ratio (SAR) was calculated for each grid cell. The SAR indicates what proportion of the cell has been dredged at least one time, calculated as:

$$\text{Swept area ratio} = \text{Area swept (km}^2\text{)} / \text{area of cell (km}^2\text{)}$$

A SAR of 1 indicates that on average each part of a grid cell has been dredged one time, a SAR of 2 indicates the whole cell has been swept twice, a SAR of 0.5 indicates that on average half of the cell has been dredged one time (or that the whole cell would be swept once every 2 years, if using one year of data to calculate the SAR).

Each VMS interpolation method (point data, SL interpolation, and cHs interpolation) was compared to the SL AIS interpolations (assumed as the truest fishing tracks) and AIS point data.

4.3.5. Data Confidentiality

VMS and AIS data are commercially sensitive, and therefore confidentiality is an important issue. Vessels that contributed to this study are anonymous throughout the analysis. VMS data were provided by fishermen under the condition that the location of fishing activity would not be displayed, therefore the spatial reference has been removed from any maps. The same level of confidentiality has been afforded to the AIS data.

4.4. Results

4.4.1. How do the basic VMS and AIS datasets compare?

The eight studied vessels recorded 129894 AIS points, and 23524 VMS points during the calendar year 2012. After cleaning, there were 89204 AIS and 15929 VMS points remaining (Figure 4.3) representing a 69% and 66% retention respectively. Of these cleaned data, 75% of the AIS data and 81% of the VMS data represented fishing points, comprising 66741 and 12581 points respectively.

Only records which had corresponding AIS or VMS data for that vessel on that day were used in the comparison analysis of fishing activity. For the comparable trip data this left 66306 AIS points and 3988 VMS points from seven vessels (thus one vessel was excluded from further analysis). This retained 99% of the cleaned AIS data and 32% of the cleaned VMS data that represented fishing points. For the matching data (i.e. only trips with a ratio of VMS:AIS within the threshold 0.8 – 1.2, to reduce missing data within trips), this was reduced to 57970 AIS points and 2587 VMS points. A substantial amount of AIS data were therefore missing, i.e. there were a lot of days for which there were VMS data but no corresponding AIS data, but there were comparable VMS records for almost all AIS records. When the data were reduced further to only trips with a high VMS:AIS ratio, 13% of the comparable AIS data and 35% of the comparable VMS data were removed. This indicates that whilst there were more missing AIS data within trips, there were also missing VMS data within trips. Both comparable and matching data were used in the analysis of fishing activity. The average time interval between all VMS points was 130 minutes, and between AIS was 13 minutes, but when only fishing points were used, the average time interval between VMS points was 114 minutes, and between AIS points was 5 minutes.

```
                          Raw Data
                          129894 AIS
                          23524 VMS

  Points not on globe    Duplicates      Points on land¹
       0 AIS               1 AIS           18432 AIS
       0 VMS               7 VMS           5702 VMS

  Points > 20 knots    Points in harbour   Pseudo-replicates
       18 AIS             22239 AIS             - AIS
       0 VMS              1886 VMS             404 VMS

                        Total Clean Data
                        AIS: 89204 [69%]
                        VMS: 15525 [66%]

                        Total Fishing Data
                        AIS: 66741 [51%]
                        VMS: 12581 [54%]

  Comparable Fishing Data           Matching Fishing Data
      AIS: 66306 [51%]                  AIS: 57970 [45%]
      VMS: 3988 [17%]                   VMS: 2587 [11%]
```

[1] Points classed as being on land are often just in harbour, but the GIS map used to define the land/harbour area may not be high enough resolution to accurately distinguish the harbour boundaries.

Figure 4.3. Preparation and cleaning of AIS and VMS data. Dashed boxes indicate data that is removed, solid boxes indicate retained data.

4.4.2. How does the assignment of fishing activity compare between VMS and AIS data?

The raw VMS data indicated 29701 hours of fishing, but the raw AIS data only estimated 7647 hours of fishing, which constitutes a substantial gap in the coverage of AIS data. Despite using data from vessels which have both VMS and AIS on-board, the AIS data only captured 26% of the time spent fishing compared to VMS data. The proportion of time each vessel spent fishing, steaming, and effectively stationary was then compared between the comparable AIS and VMS data for each vessel on each day. Whilst there was generally good correlation between AIS and VMS data, the VMS data sometimes substantially overestimated the proportion of time spent fishing, and underestimated the time spent steaming (Figure 4.4). Overall, using comparable trip data, the AIS data indicated a total of 5661 hours fishing by all vessels across the study period, and the VMS data a total of 7751 hours, suggesting 2090 extra fishing hours with the VMS than the AIS data. Overall, the AIS data

indicated a total area swept (calculated as area swept per fishing point: area swept = speed * dredge width * time) of 469km^2, and the VMS data indicated a total area swept of 651km^2.

For the matching data, the AIS data indicated a total of 4924 hours fishing across the study period, the VMS a total of 5053 hours, suggesting 129 extra hours fishing by the VMS data. The AIS data indicated an area swept of 405km^2, and the VMS an area swept of 406km^2. If using comparable data (i.e. trips for which there is some VMS and some AIS data) the overall extent of fishing footprint is under-estimated by 39% when using AIS data. However, if using only data that directly matches in time, the extent of area affected by fishing was very similar.
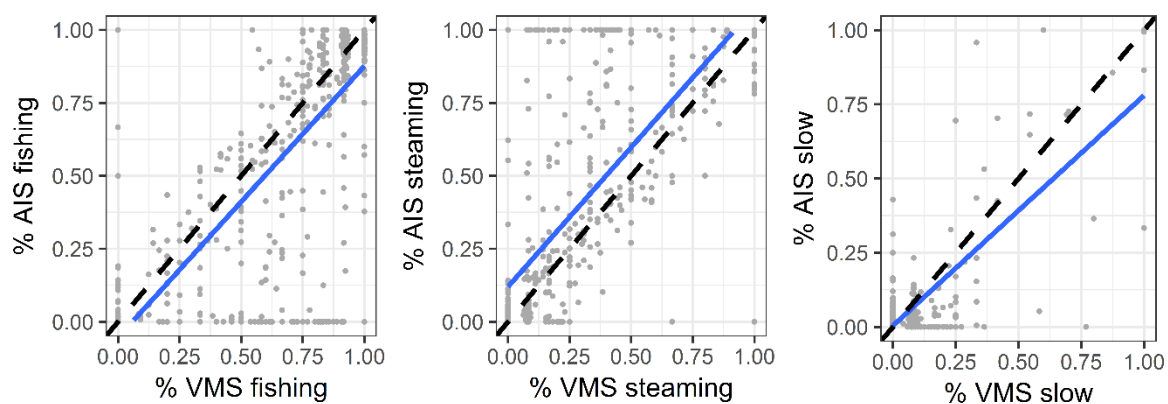
Figure 4.4. Proportion of time spent in each activity state per trip, in comparable data.

4.4.3. How does the data coverage and activity assignment differ between individuals?

A substantial amount of AIS data were missing, however the amount of missing data differed between individual vessels (Table 4.1). In all cases, more AIS data were missing than VMS data. Thus when retaining only comparable trip data, for some vessels the removal of VMS data was large, e.g. a reduction from 2176 points to 151 points (93% loss); the smallest loss was 34%. In contrast, the greatest loss of AIS data due to having no corresponding VMS data was 2%, and the smallest loss was nil. However, when using only trips with matching data (a high ratio of VMS:AIS), considerably more data were removed; 45-99% of VMS data, and 7-51% of AIS data. This suggests that overall there were substantially more AIS data missing, but there were some trips with considerable amounts of VMS data missing as well.

The comparable trip VMS data gave a higher estimate of time spent fishing and area swept than the AIS data for all individuals (Table 2). The magnitude of this difference varied between 18-92%

between individual vessels. When using the more closely matched data, the time spent fishing for each individual varied from +2% to -26%, and the area swept from +3% to -17%, but the values of the absolute difference were relatively low.

Table 4.1. Number of VMS and AIS points per vessel when using all available data, and only comparable data. Total time spent fishing and area swept by each vessel using comparable VMS and AIS data. The % dif column indicates how much smaller the AIS value was than the VMS value.

Comparable days

ID	Number of fishing points		Number of Comparable Fishing points		VMS lost	AIS lost	Time fishing		% dif	Area swept		% dif
	VMS	AIS	VMS	AIS			VMS	AIS		VMS	AIS	
1	1539	7249	616	7227	60%	0.3%	1171	646	-45%	115	64	-44%
2	1963	942	251	942	87%	0.0%	514	91	-82%	57	10	-82%
3	2176	1038	151	1036	93%	0.2%	267	96	-64%	25	9	-64%
4	1581	18086	1023	18075	35%	0.1%	1957	1521	-22%	149	117	-21%
5	1798	12291	701	12241	61%	0.4%	1328	1043	-21%	100	82	-18%
6	946	13369	620	13322	34%	0.4%	1263	1120	-11%	105	94	-10%
7	1921	13766	626	13463	67%	2.0%	1251	1145	-8%	98	93	-5%

Matching Data

ID	Number of fishing points		Number of Matching Fishing points		VMS lost	AIS lost	Time fishing		% dif	Area swept		% dif
	VMS	AIS	VMS	AIS			VMS	AIS		VMS	AIS	
1	1539	7249	259	5448	83%	25%	497	477	-4%	49	47	-4%
2	1963	942	29	460	99%	51%	58	43	-26%	6	5	-17%
3	2176	1038	40	753	98%	27%	77	69	-10%	7	7	
4	1581	18086	735	16202	54%	10%	1410	1362	-3%	107	105	-2%
5	1798	12291	463	10209	74%	17%	889	869	-2%	67	69	+3%
6	946	13369	521	12464	45%	7%	1042	1048	+1%	87	88	+1%
7	1921	13766	540	12434	72%	10%	1079	1055	+2%	84	85	+1%

The correlation between the number of VMS and number of AIS points per day varied between vessels, and depended on the data treatment (Figure 4.5), but there was a considerable amount of missing fishing data for all vessels. Using comparable trip data only, the correlation between the duration of VMS and AIS fishing records per vessel per day improved significantly. Nevertheless, the duration of AIS data is slightly lower than the VMS data for all vessels. For some vessels there is considerably less AIS data than expected on comparable days, suggesting some gaps in coverage within a trip. The dashed line indicates the 1:1 ratio between VMS and AIS data; matching data were

identified as trips that had a ratio of 0.8 – 1.2, therefore matching data showed a strong correlation between the duration of VMS and AIS points by definition (Figure 4.5c).
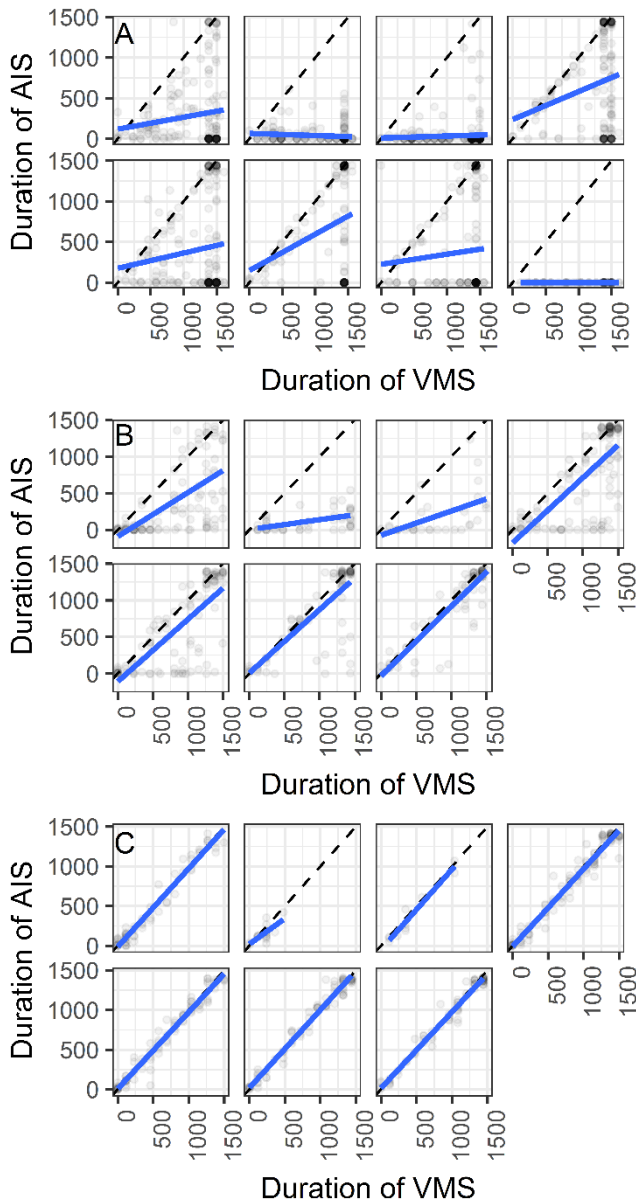
Figure 4.5. The correlation between the duration of VMS and AIS fishing points per vessel per day (A), the correlation between the duration of VMS and AIS fishing points using only data on comparable days (B), and the correlation between the duration of VMS and AIS fishing points using only data that were classed as matching (i.e. high ratio AIS:VMS) (C). Blue solid line indicates the correlation between the numbers of points per day, black dashed line indicates the 1:1 correlation. Points are translucent such that darker areas indicate a concentration of points.

4.4.4. How does the spatial footprint of fishing compare between VMS and AIS data?

4.4.4.1. Interpolation of VMS and AIS fishing tracks

Using only comparable and matching data, a straight line interpolation of the AIS data was used to create the best estimate of the vessels' tracks. The VMS data was interpolated using both the straight line (SL) and cubic Hermite spline (cHs) approach. Parameter optimisation in *VMStools* gave an *fm* parameter of 0.19, which suggested that a non-linear interpolation gave a more appropriate interpolation of the VMS tracks than a SL interpolation, based on the distance between the interpolated VMS positions and the higher frequency AIS positions.

Three days of comparable data were selected at random to display the individual interpolated tracks (Figure 4.6). From visual observation of the three different types of track interpolations (Figure 4.6), the AIS fishing tracks display shorter sections of fishing activity than with the VMS fishing tracks. The low temporal resolution of the VMS data (2 hours) may have forced the interpolations to be continuous such that they potentially missed sections of time in which fishing did not occur. In contrast, as the AIS data has a higher temporal resolution (5 minutes) it can account for shorter periods of fishing and steaming within this 2 hour window.
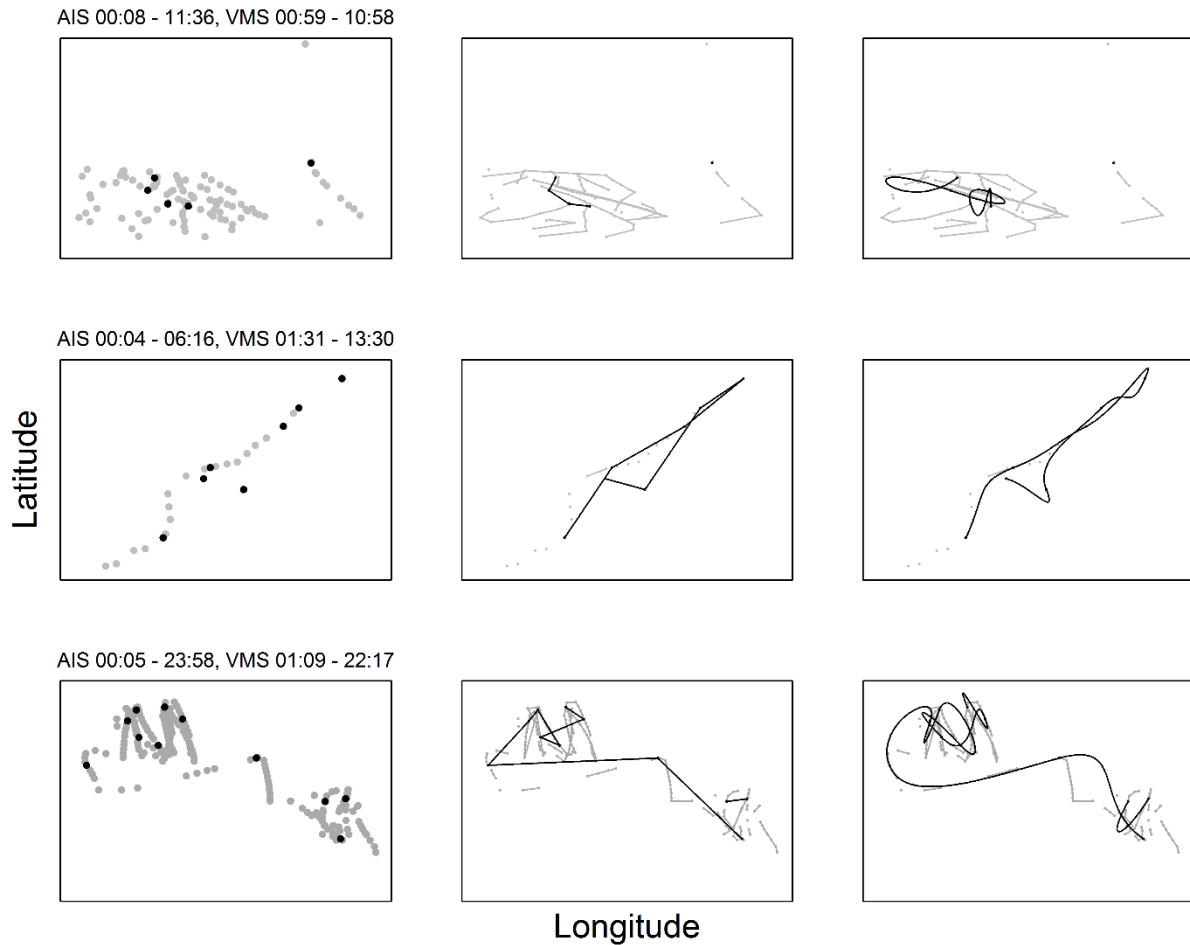
Figure 4.6. Each row = one trip by one vessel. The time span of each data set is displayed for each row. Black = VMS, grey = AIS. The first column displays the point data, the second column displays straight line (SL) interpolated data, and the third column displays the cubic Hermite spline (cHs) interpolated data for the VMS data and straight line interpolated for the AIS data. For the first trip (row 1), the VMS data appears to have underestimated the extent of fishing activity. In the second trip (row 2), the VMS data estimated a greater extent than the AIS data. In the third trip (row 3), the AIS and VMS data appear to show a similar extent, albeit with a lower resolution in the VMS tracks.

4.4.4.2. How does the extent and intensity of fishing compare?

To investigate the impact of data aggregation on the spatial extent of fishing activity, points that were classed as fishing (cf. steaming or stationary) were joined to spatial grids of varying size. Increasing the grid size for analysis increased the estimated extent of fishing activity (Figure 4.7, Table 4.2). The total extent estimates were most similar between directly matching VMS and AIS data when using the cubic Hermite spline interpolation method.

In this analysis an assumption was made that the straight line interpolation of the AIS data at a 1km grid provided the most accurate extent of fishing, as it was the highest resolution data treatment. In this case, using a 10km grid substantially overestimated the extent of fishing. Assuming the SL AIS at 1km gives the values closest to reality, the cHs interpolation of the VMS data at 1km resolution gave a very similar value for the extent of fishing, but the point VMS data at 1km greatly underestimated the extent of fishing activity. Increasing the grid size decreased the accuracy of the extent derived from AIS data, by overestimating the extent, but increasing the grid size increased the accuracy of the VMS data point data compared to the best estimate of the extent from AIS data. This suggests that the VMS data is too low poll frequency to give an accurate fishing footprint unless either points are either aggregated to a low resolution grid, or if using a high resolution (e.g. 1km) grid the points should be interpolated using a cHs interpolation. With the comparable data, using a low resolution grid buffered some of the inaccuracies associated with missing data, in terms of providing a more similar estimate between AIS and VMS data, but the total extent was substantially inflated. The method of data treatment had a substantial impact on the recorded extent of fishing (Figure 4.7). At a coarse resolution (10km grid) the method of VMS data treatment had less impact on the estimate of extent, but the overall extent estimate was significantly higher than when using a 1km grid.

The amount of the study area that was perceived as totally un-trawled (i.e. swept area ratio (SAR) = 0) decreased as the grid size increased (Figure 4.8). The SAR values were considerably more similar between data treatments using the matching data than the comparable data. Using matching data with a 1km grid, the area trawled 0.1 times (i.e. grid cells that would on average have been trawled completely every 10 years) varied by about 500km^2 between the data treatments (all fishing activity recorded by the matching AIS data at a 1km grid covered a total extent of 6500km^2). Only directly matching data from 7 vessels over 12 months was used, therefore although the value is relatively low, if scaled up to a fleet and using more complete data, these differences would be multiplied. However, a 3km grid showed little variation in the pattern of fishing intensity between each data treatment. A larger grid therefore buffered some of the inconsistencies in fishing intensities between the data treatments, but reduced the area of the seabed that was perceived as unfished. There is a trade-off between using a grid of higher resolution to improve the extent estimate and using a grid of lower resolution to improve the accuracy of the intensity estimates.
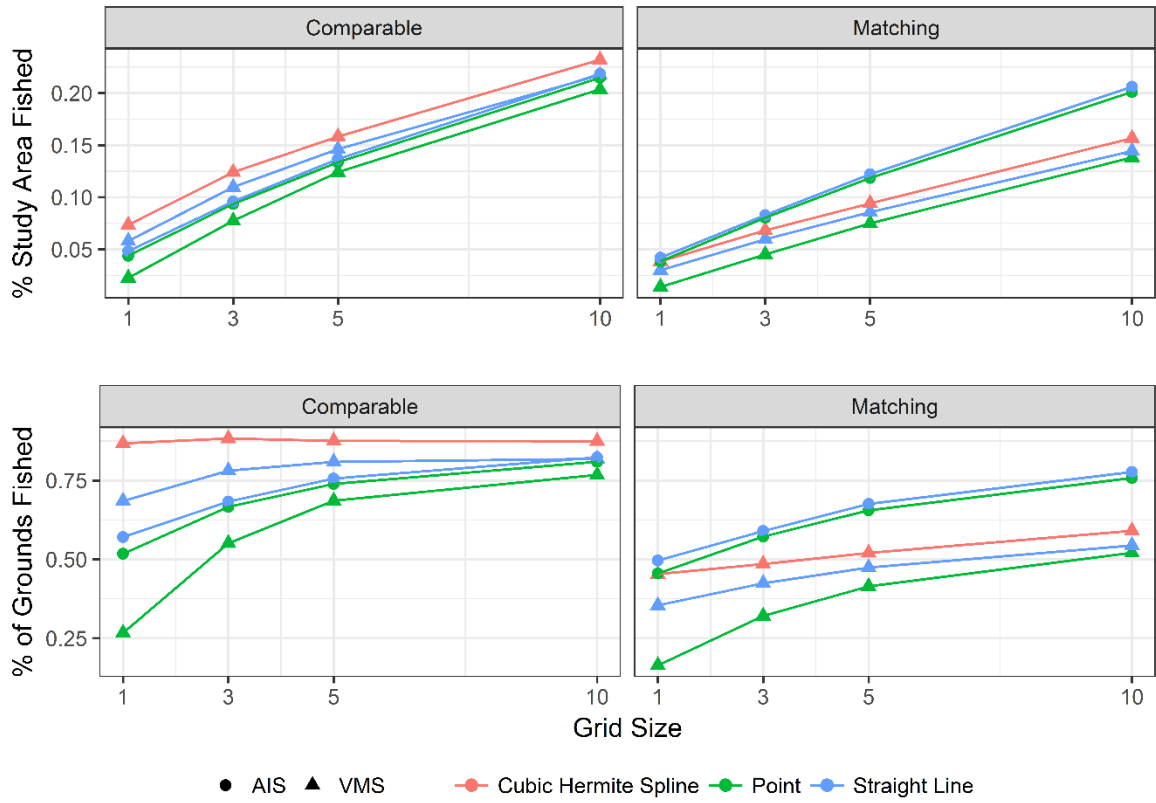
Figure 4.7. Comparison of the extent of fishing activity across the whole study area using each interpolation method, and the extent of fishing activity across fishing grounds (i.e. only areas which had recorded fishing activity by any of the data).
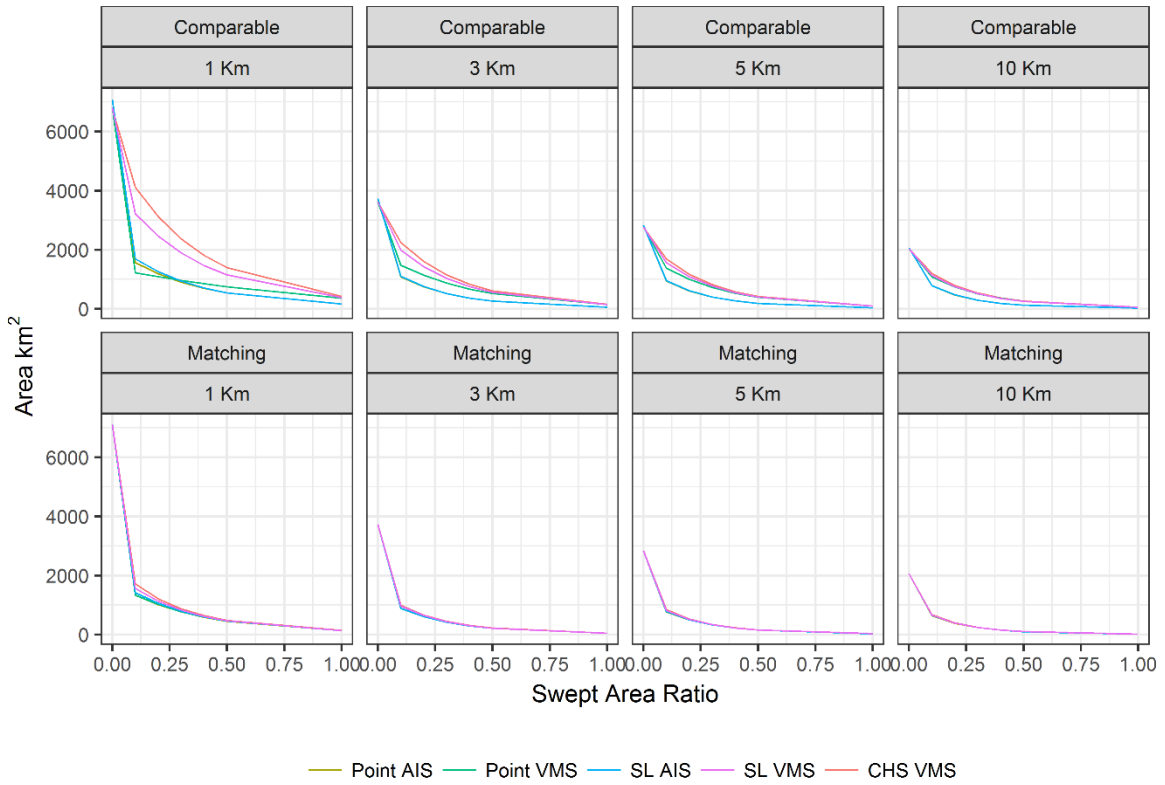
Figure 4.8. The area of seabed swept 0 – 1 times during the study period, by grid size (1, 3, 5, and 10km), by data type (comparable or matching), and using each method of data interpolation (point, SL and cHs).

Table 4.2. Comparison of VMS and AIS data using different interpolation methods at different spatial scales. Difference column indicates how much larger or smaller the extent was using AIS data, in km², and the percentage difference indicates the difference as a percentage of the study area.

	Grid Size	Comparable VMS			Comparable AIS			Dif. (km²)	% dif	% dif grounds	Direct match VMS			Direct Match AIS			Dif. (km²)	% dif (study area)	% dif (grounds)
		Extent (km²)	% of study area	% of grounds	Extent (km²)	% of study area	% of grounds				Extent (km²)	% of study area	% of grounds	Extent (km²)	% of study area	% of grounds			
P	1km	1831	2	27	3553	4	52	1722	2	25	1127	1	16	3123	4	46	1996	2	29
	3km	6273	8	55	7587	9	67	1314	2	12	3654	5	32	6516	8	57	2862	4	25
	5km	10050	12	69	10825	13	74	775	1	5	6075	8	41	9600	12	66	3525	4	24
	10km	16500	20	77	17400	21	81	900	1	4	11200	14	52	16300	20	76	5100	6	24
SL	1km	4702	6	69	3917	5	57	-785	1	11	2432	3	35	3407	4	50	975	1	14
	3km	8892	11	78	7776	10	68	-1116	1	10	4833	6	42	6714	8	59	1881	2	17
	5km	11850	15	81	11075	14	76	-775	1	5	6950	9	47	9900	12	68	2950	4	20
	10km	17600	22	82	17700	22	82	100	0.1	0.5	11700	14	54	16700	21	78	5000	6	23
cHs	1km	5953	7	87							3111	4	45				296	0.4	4
	3km	10053	12	88							5526	7	49				1188	1	10
	5km	12825	16	88							7625	9	52				2275	3	16
	10km	18800	23	87							12700	16	59				4000	5	19

4.5. Discussion

Neither VMS nor AIS were designed as tools to aid our understanding of fisheries science, but whilst both data sources offer valuable data for understanding fishing activity, their use must be based on an informed understanding of the most appropriate way to process and interpret the data. Of greatest importance, AIS data can have a substantially lower coverage than VMS data and thereby provides a potential underestimate of overall activity (Russo et al., 2016, Natale et al., 2015). This study has contributed to this understanding by demonstrating how even when only looking at VMS and AIS from the same individual vessels (i.e. accounting for the lower fleet coverage of AIS), and even reducing it to concurrent data within those individuals' fishing activity, there remain differences in the perceived fishing activity with each data source.

4.5.1. Can AIS data be an appropriate fisheries monitoring tool?

Whilst AIS data is attracting attention as a promising tool for analysing fishing activity, because it provides publicly available high resolution vessel tracking data, the gaps in its coverage present a substantial hurdle. In this study considerable gaps in the coverage of AIS data compared to the VMS data were found, which concurs with similar studies (Russo et al., 2016, Natale et al., 2015). A similar proportion of VMS and AIS data were retained following data cleaning (i.e. removing incorrect coordinates, points on land, points in harbour etc.), but after only comparable days were retained (i.e. days for which there were both VMS and AIS for a vessel) only 32% of VMS fishing points were retained for analysis. This was further reduced to 11% when only highly matching data were retained. This retention also varied substantially between individual vessels, with 7 – 60% retention of VMS data when using only comparable days, and 1 – 55% when using only matching data; for one vessel, on 93% of days for which there were VMS fishing points, there were zero AIS fishing points, and no directly matching AIS data for 99% of the VMS. For the whole of the studied fleet, this translated as AIS data capturing only 26% of the duration of fishing activity captured by VMS data in 2012.Clearly, this is a substantial gap in the AIS data coverage, and would be a cause for concern if using AIS data to analyse fishing activity without VMS data. It is likely inappropriate to use AIS data for absolute estimates of fishing footprints or intensity, because the gaps in coverage are too substantial, but more comparative studies may be possible. However, caution could be required when using historical AIS data compared to more recent or future AIS data, where compliance or technological advances may potentially lead to higher coverage.

Aside from addressing the more technical limitations to spatial coverage (Natale et al., 2015, Russo et al., 2016), these results support the suggestions from McCauley et al., (2016) that to gain the full benefits of AIS data for fisheries science, policy interventions would also be required, for example, to reduce the gaps in AIS coverage from fishers turning down the AIS transmitter. There are, however, two principle reasons why fishers may wish to conceal their activity from an AIS system; 1) detection avoidance whilst undertaking illegal fishing activity, and 2) preventing other fishers from using AIS data to identify prime fishing grounds. Real time AIS data is openly available to view, including to other fishermen, so it is understandable that fishermen may be reluctant for such high resolution tracking data to be openly and instantaneously available, due to the commercial sensitivity of such data. It is difficult to envisage how this issue would be overcome. If it became a legal requirement that the AIS unit was functioning at full strength and an openly available high resolution high coverage dataset of fishing activity was achieved, it could lead to conflict or negative economic consequences for fishers.

4.5.2. Fishing activity differed between VMS and AIS data when using directly comparable data.

When only using data from comparable days, there were differences in the fishing activity derived from VMS and AIS data. The VMS data overestimated the time spent fishing and area swept compared to the AIS data. However, once data were reduced to the matching data, these values were more similar with only 129 extra fishing hours according to the VMS data. On comparable days (i.e. days when there was some VMS and AIS for a particular vessel), the differences were therefore largely due to missing AIS data, but when using only more closely matching data, the smaller difference in recorded fishing duration could be related to the bias from a 2 hourly ping rate of VMS data. Nonetheless, even with directly matching data this constituted 10 extra days of fishing with VMS data (assuming 12 hours continuous fishing per day), or 3% of the total fishing hours recorded. At a small scale of 7 vessels over 1 year of fishing, this is a small value, but scaled up to a whole fleet across multiple years, this could represent substantial fishing effort. The temporal resolution of the VMS data may have missed the shorter hauling/moving sections in between scallop dredge tows, which would be less than two hours in duration, and could therefore overestimate the fishing effort. Identifying fishing activity is much more sensitive under VMS than AIS data, as you could incorrectly classify a 2 hour time frame as fishing or non-fishing, whilst with AIS you would only misclassify seconds or minutes. Technology that would provide information on when the gear is in the water

would improve estimates of scallop fishing activity and would address one of the issues of poll frequency for VMS.

The methodology used to analyse the data altered the patterns seen in fishing intensity. As the grid size for analysis increased, the perceived extent of fishing activity increased (Dinmore *et al.*, 2003; Hinz *et al.*, 2013; Piet and Quirijns, 2009; Piet and Hintzen, 2012); this impact of grid size was greater when the data was at a lower poll frequency. If the SL AIS data is assumed to provide the best estimate of extent, the point VMS data underestimated the extent by two thirds, the SL VMS underestimated the extent by one third, but the cHs VMS suggested an extent similar to the AIS. Using the high resolution AIS data there was little difference between the extent of the point data and SL data, regardless of grid cell size. However, when using a 1km grid the extent indicated by VMS point data was half that of the SL VMS data, and a third of the cHs VMS data. As the grid size increased, this disparity decreased. If using point VMS data, it therefore may not be appropriate to use a grid smaller than 3-5km when estimating extent, unless points are interpolated.

When providing VMS data in an aggregated format, it is likely not appropriate to provide it at a grid resolution less than 3km by 3km, unless the data has been interpolated, because the extent would be underestimated. Nevertheless, providing data aggregated at a low resolution can overestimate the extent of fishing activity. When considering the influence of these factors on fishery management options, there is the need for a balance between data cost (i.e. resolution) and accuracy of the results. Over-estimation of the impacted area may result in more draconian action than is necessary whereas underestimation of the impacted area, whilst of short term benefit to the industry may have longer term repercussions for sustainability. VMS is often only available in an aggregated format due to confidentiality issues, which can overestimate the extent (Hinz et al., 2013). The poll frequency also intuitively influences the need to interpolate the data. When using high poll frequency data, such as AIS data, interpolation is perhaps not necessary, especially when using a lower resolution grid for analysis. However, when using lower poll frequency VMS data, the grid size and the method of interpolation can have a substantial impact on the perceived fishing footprint. Highly aggregated VMS data at coarse resolutions is highly limiting in the ability of science to draw reasonable conclusions about fishing footprints and impacts (Hinz *et al.*, 2013).

4.5.3. Predicting unpredictable scallop dredging activity

The issues associated with interpolating low poll frequency VMS data are particularly relevant to scallop dredging, due to the idiosyncratic movements of the vessels, such as sharp turns and re-

towing over the same areas, which may be missed by the lower resolution VMS data (Lambert et al., 2012). The optimal *fm* parameter (a parameter that determines how much the tracks should curve in a cHs interpolation) was markedly different in this study compared to that undertaken by Lambert et al., (2012) with scallop dredgers in the Isle of Man. They concluded that the optimal *fm* parameter was close to zero, i.e. a straight line. Here an optimal fm parameter of 0.19 was reported, which is considerably different from a straight line. For scallop dredgers, and in other fisheries with shorter haul durations, the availability of a higher resolution dataset is perhaps even more important (c.f. trawlers) due to the unpredictable movement patterns associated with these fisheries.

This study has provided a strong argument for the creation of comprehensive positional information at higher temporal resolution than is currently available in order to make robust estimates of fishery activities in space and time. This could be achieved through either increased polling frequency on VMS units, the more rigorous implementation of AIS units, or through partnership agreements between the scallop industry and scientists. The fishing extent according to the VMS data was variable compared to the AIS data. At a finer scale grid, the VMS data underestimated extent compared to AIS data, indicating that it is not appropriate to use a fine scale 1km grid when analysing VMS point data. The grid size used for analysis and the method of interpolation had a more substantial impact on the perceived fishing activity when using the lower poll frequency VMS data than the higher poll frequency AIS data. Increasing the poll frequency of VMS data would therefore buffer the impacts associated with these methodological considerations.

Often VMS is only available to scientists in aggregated 3nm cells, which is roughly 5km cells; in this case there could be a significant benefit to having AIS data, because the fishing extent may be half of that suggested from the aggregated VMS data. Nevertheless, the gaps in coverage prevent AIS data from being a viable alternative. It is not appropriate to simply provide VMS point data aggregated to a higher resolution of 1km grid cells, because this underestimated the extent of fishing activity, due to the low temporal resolution of data points. One solution to reducing temporal gaps in the VMS data could be to interpolate the VMS data which could then allow aggregation to 1km cells. Interpolation of 2 hourly VMS pings would, however, be unable to resolve the more complex fishing tracks that some scallop vessels follow. The solution which offers the optimal increase in data accuracy, and therefore accuracy of footprint estimation would be to increase the rate at which VMS data are collected (i.e. higher polling rates).

4.6. Conclusions

The present study demonstrated the utility of having access to more frequently polled vessel position data. McCauley et al., (2016) described AIS as currently a 'service that best observes vessels that don't mind being seen'. This likely arises from a lack of desire to be seen by competing vessels and in some cases may be linked to legal infringements. Nonetheless, VMS already provides a means of collecting such data in a manner shielded from public view and hence represents an appropriate pathway for the more accurate calculation of fishing footprints through increased polling rates. At present, given the current frequency of VMS polling there remains the potential for over-reporting of fishing effort leading to a worse assessment of the state of the marine environment in relation to this metric. As AIS was developed for the purpose of safety and collision avoidance, unless additional regulations are introduced, designed specifically to increase the coverage of fishing activity, it seems unlikely that AIS data could be considered as an equal alternative to VMS data. If the gaps in coverage were addressed, the increased poll frequency of AIS data would allow more accurate analysis of fishing activity, but increasing the poll frequency of VMS data may be a more viable option. The use of reliable high resolution AIS or VMS data would ultimately benefit fishers and scientists, through generating more accurate fishing footprints and a better understanding of the ecosystem impacts of fishing, and thus more sustainable management.

4.7. Acknowledgements

4.8. References

Campbell, M. S., Stehfest, K. M., Votier, S. C., and Hall-Spencer, J. M. 2014. Mapping fisheries for marine spatial planning: Gear-specific vessel monitoring system (VMS), marine conservation and offshore renewable energy. Marine Policy, 45: 293–300.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES Journal of Marine Science, 60: 371–380.

EC. 2009. Council Regulation (EC) No. 1224/ 2009 of 20 November 2009 Establishing a Community control system for ensuring compliance with the rules of the Common Fisheries Policy, amending Regulations (EC) No. 847/96, (EC) No 2371/2002, (EC) No. 811/2004, (EC) No.

Eigaard, O. R., Bastardie, F., Hintzen, N.T., Buhl-Mortensen, L., Buhl-Mortensen, P., Catarino, R., Dinesen, G. R. 2016. The footprint of bottom trawling in European waters: distribution, intensity and seabed integrity. ICES Journal of Marine Science.

FAO, 1998. Fishing operations. 1. Vessel monitoring systems. *FAO Technical Guidelines for Responsible Fisheries,* No. 1, Suppl. 1. Rome, FAO. 58p.

Hintzen, N. T., Piet, G. J., and Brunel, T. P. A. 2010. Improved estimation of trawling tracks using cubic Hermite spline interpolation of position registration data. Fisheries Research, 101: 108 - 115.

Hintzen, N. T., Bastardie, F., Beare, D., Piet, G. J., Ulrich, C., Deporte, N., Egekvist, J., *et al.* 2012. VMStools: Open-source software for the processing, analysis and visualisation of fisheries logbook and VMS data. Fisheries Research, 115–116: 31–43.

Hinz, H., Murray, L. G., Lambert, G. I., Hiddink, J. G., and Kaiser, M. J. 2013. Confidentiality over fishing effort data threatens science and management progress. Fish and Fisheries, 14: 110–117.

Joo, R., Salcedo, O., Gutierrez, M., Fablet, R., and Bertrand, S. 2015. Defining fishing spatial strategies from VMS data: Insights from the world's largest monospecific fishery. Fisheries Research, 164: 223–230.

Kaiser, M., Clarke, K., Hinz, H., Austen, M., Somerfield, P., and Karakassis, I. 2006. Global analysis of response and recovery of benthic biota to fishing. Marine Ecology Progress Series, 311: 1–14.

Kaiser, M. J., Hilborn, R., Jennings, S., Amaroso, R., Andersen, M., Balliet, K., Barratt, E., *et al.* 2016.

Prioritization of knowledge-needs to achieve best practices for bottom trawling in relation to seabed habitats. Fish and Fisheries, 17: 637–663.

Lambert, G. I., Jennings, S., Hiddink, J. G., Hintzen, N. T., Hinz, H., Kaiser, M. J., and Murray, L. G. 2012. Implications of using alternative methods of vessel monitoring system (VMS) data analysis to describe fishing activities and impacts. ICES Journal of Marine Science, 69: 682–693.

Lee, J., South, a. B., and Jennings, S. 2010. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES Journal of Marine Science, 67: 1260–1271.

Mccauley, B. D. J., Woods, P., Sullivan, B., Bergman, B., Jablonicky, C., Roan, A., Hirshfi, M., *et al.* 2016. Ending hide and seek at sea. Science, 351: 1148–1150.

Murray, L. G., Hinz, H., Hold, N., and Kaiser, M. J. 2013. The effectiveness of using CPUE data derived from Vessel Monitoring Systems and fisheries logbooks to estimate scallop biomass. ICES Journal of Marine Science, 70: 1330–1340.

Murray, L., Hinz, H., and Kaiser, M. 2011. Functional response of fishers in the Isle of Man scallop fishery. Marine Ecology Progress Series, 430: 157–169.

Natale, F., Gibin, M., Alessandrini, A., Vespe, M., and Paulrud, A. 2015. Mapping fishing effort through AIS data. PLoS ONE, 10: 1–16.

Piet, G. J., and Quirijns, F. J. 2009. The importance of scale for fishing impact estimations. Canadian Journal of Fisheries and Aquatic Sciences, 66: 829–835.

Piet, G. J., and Hintzen, N. T. 2012. Indicators of fishing pressure and seafloor integrity. ICES Journal of Marine Science, 69 (10): 1850 - 1858.

Russo, T., D'Andrea, L., Parisi, A., Martinelli, M., Belardinelli, A., Boccoli, F., Cignini, I., *et al.* 2016. Assessing the fishing footpring using data integrated from different tracking devices: Issues and opportunities. Ecological Indicators, 69: 818–827.

Stelzenmuller, V., Rogers, S. I., and Mills, C. M. 2008. Spatio-temporal patterns of fishing pressure on UK marine landscapes, and their implications for spatial planning and management. ICES Journal of Marine Science, 65 (6): 1081: 1091.

CHAPTER 5: An Individual-based Model of the Isle of Man Scallop Fishery

Overview, Design Concepts, and Details (ODD) Model Description

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Human behaviour is an area of considerable uncertainty in fisheries management (Fulton *et al.*, 2011). Failing to account for the behavioural response of fishermen to management can lead to unintended consequences of management, and even produce negative environmental, economic, or social effects (Hilborn *et al.*, 2004; Pascoe and Mardle, 2005; Dinmore *et al.*, 2003). Individual-based models (IBMs) could help to address some of the knowledge gaps in our understanding of fisher behaviour, and allow us to create simulation tools that could help both managers and fishers better predict and understand the potential consequences of different management scenarios (Evans, 2012; Grimm and Railsback, 2005).

Optimal Foraging Theory (OFT) (MacArthur and Pianka, 1966) has been demonstrated as a suitable framework for investigating fisher behaviour (Begossi, 1992; Begossi *et al.*, 2009; de Oliveira and Begossi, 2011; Lee *et al.*, 2014; Sosis, 2002). Nevertheless, there may be violations to some of the assumptions of OFT; namely that all fishers do not have equal abilities, fishers may not have complete knowledge of catch rates in the system, and importantly, not all fishers may be true profit maximisers (Chapter 2, Chapter 3). An IBM provides a more flexible framework within which to account for deviations from such theory (Grimm and Railsback, 2005). Understanding more about how to realistically predict fisher foraging behaviour could allow the development of simulation tools that are better able to predict the outcome of management, reducing unexpected, or unintended, outcomes of management.

An individual-based model (IBM) of fishing activity in the Isle of Man scallop fishery was therefore developed, based on simple foraging theory, and an understanding of the system gained from analysis of questionnaire interview data (Chapter 2) and vessel monitoring system and logbook data (Chapter 3). The ultimate aim of the model was to predict the outcome of different closed area management scenarios. Initially, however, the model was designed to understand the extent to which we can predict fishing activity, deviations from optimal foraging models, and what model structures provide the most realistic simulations of fishing activity. This model description follows the standardised Overview, Design concepts, Details (ODD) protocol for describing individual-based models (Grimm *et al.*, 2006, 2010). Further details of the model development and validation are presented in Chapters 6 and 7.

5.1. Purpose

The purpose of this model is ultimately to explore the potential impact of different management measures on the Isle of Man scallop fishery from an environmental and economic perspective, in terms of the footprint of fishing and the economic impacts on fishing vessels. In particular, it is designed to understand how the spatial extent and arrangement of closed areas affects the fishers' profits and the amount/proportion of the scallop biomass removed in a season. For example, if we close an area to scallop dredging, where would fishers go instead (displacement of effort) to compensate for this lost area, what would the environmental impacts of this shift be, and would the fishers still be able to make enough money to remain as a viable business?

Initially, however, the model was used to understand the extent to which we can predict fishing activity. There are four main decisions that fishers make in the model: 1) If they should fish that day; 2) the location to which they should steam to begin fishing at the start of the day; 3) after completing a tow, whether they remain on that patch or move to a new location; and 4) when they should return to port. These decisions can be made in different ways; the first stage of model development is to determine what behavioural rules best recreate the fishery. For example, if, in the model, fishers select a patch in which to fish based purely on the highest expected catch rate, is this more or less realistic than if they take account for the travel cost when deciding where to fish?

5.2. Entities, State Variables and Scales

The model has three entities: the global fishery entity, fishing patches, and fishing vessels. The fishery is attributed with management variables including total allowable catch (total catch limit in one season), individual daily catch limits, the curfew hours, the market price of scallops, the fuel prices, number of dredges permitted, and the number of vessels (Table 5.1).

Table 5.1. State Variables of the Fishery. These state variables are defined, in part, by the fishery regulations that currently apply in the Isle of Man.

Category	Variable	Description
Monitors	Date	Current date in the model simulation
	Time	Current time in the model simulation
	CatchSoFar	Total catch so far in the simulation
	FishingExtent	The number of cells that have been fished, within the 12nm limit of the territorial sea
Regulations	Total Allowable Catch	Total catch weight allowed by all vessels within the simulation year
	Individual Daily Catch Limit	Total amount each individual vessel is allowed to catch per day
	CurfewHours	The total number of hours a vessel is allowed to fish per day
	MarketPrice	The price a vessel receives per kg of scallops
	FuelPrice	The cost of a litre of fuel
	DredgeLimit	The maximum number of dredges any vessel can be initialised with
	DredgeLimit3nm	A regulation for the maximum number of dredges permitted within 3nm of shore
	DredgeLimit12nm	A regulation for the maximum number of dredges permitted within the 12nm Sea

The patches make up a square grid landscape of 28 by 33 patches, each of which are 3km by 3km. The total extent of the model is 84km by 99km, which corresponds with the area in which vessel monitoring system (VMS) data was available to compare the model output to. Grid cells of 3km were used as a compromise between maximising the accuracy of the calculation of the extent and intensity of fishing activity (Lambert *et al.*, 2012). Grid cells are characterised by a scallop biomass and corresponding expected catch rate, and a distance to port. The cell biomass is depleted as vessels fish in the cell. For all patch attributes, and their description, see Table 5.2.

Table 5.2. State variables which define the characteristics of each grid cell in the model environment.

Category	Variable	Description
Cell Location	gridID	The ID number of the grid cell
	Easting	Easting of cell midpoint
	Northing	Northing of cell midpoint
	IsLand?	Whether the cell is land
	IsPort?	Whether the cell is a port
	In12nm?	Whether the cell is within the 12nm territorial sea
	IsClosed?	Whether the cell is 'closed' to fishing
	DougDist	Distance of the cell to the port of Douglas[1]
	PeelDist	Distance of the cell to the port of Peel[1]
	RamseyDist	Distance of the cell to the port of Ramsey[1]
	PtStMaryDist	Distance of the cell to the port of Port St Mary[1]
	Ground	Whether the cell is part of Targets, Chickens, East Douglas, or Point of Ayre fishing grounds.
Scallop Catches	BiomassPerM2	Scallop biomass per m^2 as calculated in the scientific survey (Bloor et al., 2012). Dynamic variable that is updated according to fishing depletion.
	CellBiomass	Total cell scallop biomass derived from scientific survey data
	EffortTrend	Long term trend in fishing effort seen in this cell, as an indicator of the suitability of the cell for fishing (i.e. habitat, depth, long term scallop abundance)
	TowCount	Record of fishing effort in the cell throughout the simulation
	ExperiencedCpues	A list of the CPUE each vessel has experienced in this cell
	CatchFromPatch	The scallop weight caught from this patch
	Vms_12_13_catch	Landings recorded from VMS and logbook data in each cell in the 2012-2013 scallop fishing season, against which the model output can be compared. These are changed to data from the 2013 – 2014 or 2014 – 2015 fishing season as required.
	Vms_12_13_effort	Fishing effort recorded from VMS data in the 2012-2013 scallop fishing season, against which the model output can be compared. These are changed to data from the 2013 – 2014 or 2014 – 2015 fishing season as required.
Patch choice decision	UtilityScore (12 scores, for each strategy (3) from each port (4)	A utility score is calculated for each cell, relevant to each fisherman's strategy, derived from the distance to port and cell biomass. Used in the conjoint analysis patch choice decision.

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[1] Straight line distances would allow vessels to travel across the land, therefore these distances reflect actual travel routes, from a cost distance raster that accounts for the travel distance around the land.

There are 3 types of fishing vessels (EFF, QTM and QLM, which correspond to behavioural strategies identified during questionnaire surveys (Chapter 2; Shepperson *et al.*, 2016). Vessels are characterised by state variables of home port and vessel size (vessel capacity unit (VCU)). Home port determines the spatial location at which each vessel is based, and therefore largely determines the fishing ground prosecuted by the vessel. The number of vessels of each type in each port were determined from logbook records, to represent the ratios of the number of trips observed from each port in the fishery. The vessel size determines the amount of fuel used, and the absolute catch rates of each vessel, because larger vessels tend to utilise more dredges. For all vessel attributes see Table 5.3.

Table 5.3. State variables which define the characteristics of the individual fishing vessels in the model.

Category	Variable	Description
Physical Characteristics	VCU	Vessel capacity unit, a measure of vessel size that accounts for the length, breadth and engine power of the vessel.
	NumberOfDredges	Number of dredges towed by the vessel, calculated from the VCU.
	DistancePerTick	The distance the vessel can travel in 1 time step during the model
	HoldingCapacity	Maximum hold capacity for scallop catch
	Breed	Individuals in the model can be 'vessels' i.e. a fishing vessel from the Isle of Man, who is fully simulated, or 'externals' i.e. vessels from outside of the IOM who are not fully simulated.
Financial Variables	FuelPerSteam	Fuel used per steaming tick, calculated from VCU
	FuelPerTow	Fuel used per towing tick, calculated from VCU
	GrossTarget	Minimum threshold catch target to inform the vessel's decision to return to port
	GoodGross	Gross revenue that was considered as a good day of fishing.
Behavioural Variables	Strategy	The behavioural strategy of each vessel as determined from the conjoint analysis.
	SteamSpeed	The speed at which the vessel steams, in kmph.
	TowSpeed	The speed at which the vessel tows, in kmph.
	MaxFishHours	Maximum possible time the vessel will fish for.
	MaxTripDuration	Maximum possible time the vessel will stay at sea.
	HandlingTime	Minimum possible time between two consecutive tows (time spent emptying the nets)
	MaxDistance	The maximum distance from port the vessel can/will operate.
	GivingUpRate	The minimum catch rate that the vessel considers economically viable.
	SeaStateTolerance	The maximum possible sea state the vessel can fish in
	MyPort	The port the vessel primarily uses.
	ChanceOfFishing	The chance that each vessel will head to sea each day, to reflect the number of trips observed in previous logbook records.
	Patch-choice-decision	The decision rules the vessel follows depending on the model settings
	Between-patch-decision	The decision rules the vessel follows depending on the model settings
	Return-decision	The decision rules the vessel follows depending on the model settings
Activity during simulation	CurrentActivity	The 'activity' the vessel is currently performing: InPort, Steaming, Towing, Moving, or Returning

	TripNumber	A counter for the number of trips taken in each simulation
	HoldStatus	How many scallops are stored aboard at the current time.
	DistanceToPort	The distance of the vessel to its port.
	ChosenGround	The patch that the vessel is currently steaming towards.
	ReceivedCpue	The CPUE that a vessel receives during towing activity
	TimeSteaming	The time spent steaming during this trip
	TimeTowing	The time spent towing during this trip
	TimeHandling	A monitor of the current amount of time spent handling
	TimeHandlingTrip	The total time spent handling per trip
	Visited-patches	A list of the patches visited.
	Catch-rates	A list of the catch rates received
	TripDuration	Duration the vessel has been at sea
	FishHours	Duration since towing activity began
	TimeOnPatch	The time a vessel has spent on its current patch
	NextGround	Once at sea fishing, the patch a vessel decides to move to
	PatchDist	The straight line distance from port to the chosen patch
	RealDist	The travel distance from port to the chosen patch, i.e. accounting for travel around land.
	Adj-distancepertick	The distance a vessel can travel per tick, adjusted so that it travels in a straight line at a speed that would allow it to arrive at the chosen cell at the same time had it been travelling along the real route, i.e. avoiding land.
	Xx	The x coordinate of the vessel's port
	yy	The y coordinate of the vessel's port
	Patches-seen	The patches a vessel can choose between when selecting where to fish.
	Expected catch	The catch a vessel expects to catch based on the scallop biomass and the area swept
Vessel Monitors	Received catch	The catch a vessel receives, which is drawn from a normal distribution with mean of the expected catch and a standard deviation of 10% of the expected catch.
	TotalCatch	The vessel's total catch
	TotalTowing	The total time a vessel has spent towing
	TotalSteaming	The total time a vessel has spent steaming
	TotalHandling	The total time a vessel has spent handling
	TotalTime	The total time a vessel has spent at sea
	TotalFuelCost	The vessel's total fuel cost
	TotalValue	The vessel's total catch value
	TotalProfit	The vessel's total profit
	TotalDist	The total distance travelled by a vessel

There are 'External' (i.e. non-Manx vessels) in the model, which are essentially simplified versions of the Manx vessels. These vessels appear at the start of a day, deplete cells, and disappear at the end of the day. The catches by External vessels are recorded as a total sum; individual External vessels are not tracked or recorded. For all External vessel attributes see Table 5.4.

Table 5.4. State Variables that characterise the External fishing vessels in the model

Category	Variable	Description
Physical Characteristics	Ex-vcu	The size of the vessel, drawn from a random distribution based on the distribution of VCUs in logbook records made by external vessels
	Ex-NumberOfDredges	Number of dredges derived from the VCU
Activity during simulation	External-state	The current behavioural state the vessel is in (towing or moving)
	External-catch	The amount caught
	Ex-timetowing	The time spent towing
	Ex-timeactive	The time spent active (i.e. towing and moving)

The model uses 4 minute time steps, as it takes a vessel approximately 4 minutes to steam 1km (when not fishing, which happens at a slower speed). The model runs for 7 months (1 fishing season), where a day consists of 360 ticks (24 hours), and months take a simplified form of 30 days each.

5.3.   Process Overview and Scheduling

This section outlines the processes in the model and the order in which they are executed. It is designed to provide an overview of the model function, explain the order of processes, and how individuals operate. Full details of processes are provided in the submodels section.

Vessels operate in daily fishing trips, returning to port at the end of each simulation day. At any one time fishing vessels can have one of five 'activity states': tied up in port, steaming from port to an initial patch, towing dredges (i.e. fishing), moving between patches, or returning to port. During each model tick fishing vessels are instructed to perform their current activity. At the beginning of a simulation day all vessels are in port, and must decide whether they will go to sea on that day (Figure 5.1). If a vessel does not go to sea, it remains in port for the rest of that simulation day. If a vessel decides to go to sea it will select a target fishing patch, and change to the steaming activity state. Vessels in the steaming activity state are travelling from port to their chosen fishing patch.

Once a vessel reaches its chosen fishing patch it will change its activity status to towing and begin to catch scallops. When a vessel completes a tow on a patch, the scallop biomass is depleted accordingly, and the cell colour is updated to reflect how many fishing events have occurred in it. At the end of each tow, the vessel will decide if it is to remain on this patch towing, to move to a new patch to tow, or to return home. The vessel either remains in the towing activity state and completes another tow on its current patch, sets its heading to a new patch and changes to the moving between patches activity state, or it changes to the returning to port activity state. The rules by which a vessel makes each of these decisions depends on which behavioural settings have been chosen (see details in submodel section).
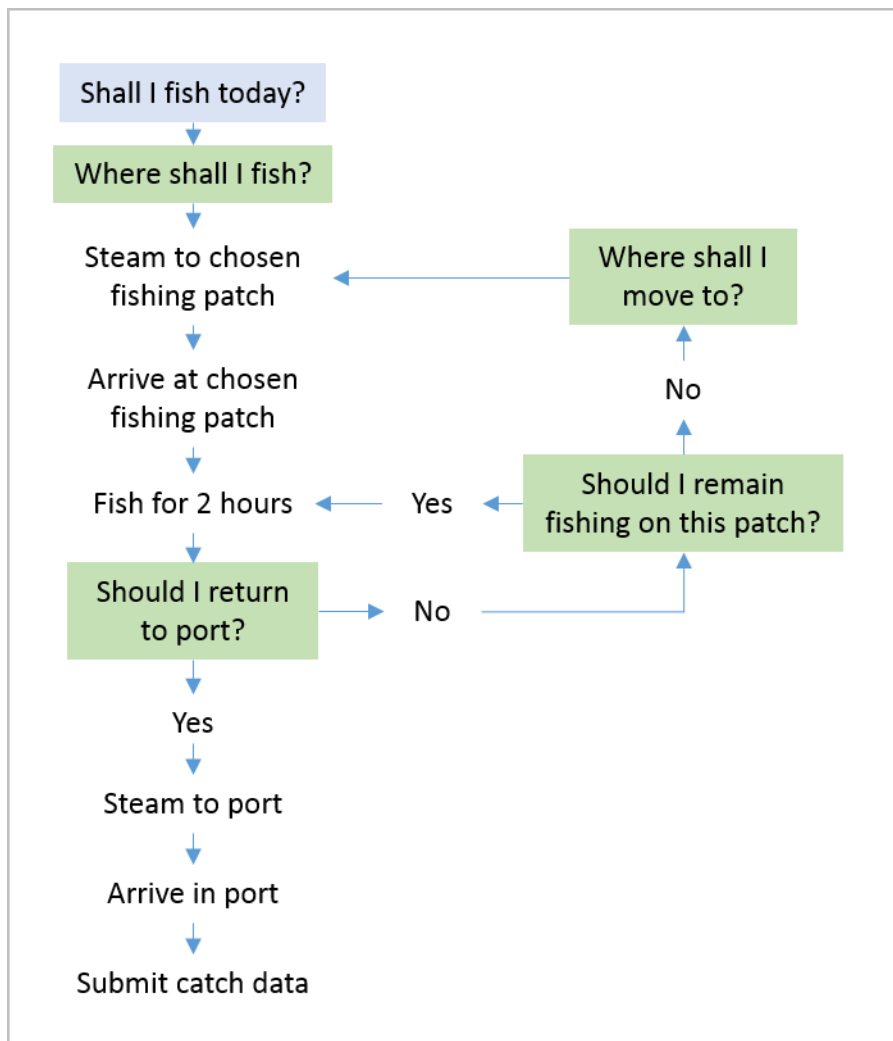
Figure 5.1. Flowchart for decision process made by vessels in the model

Regardless of the 'return to port' behavioural rules they are following, vessels evaluate whether their trip duration has exceeded the maximum possible time they can/will stay at sea, as stated in a

questionnaire survey. If so, they change their activity to returning to port. Once a vessel reaches port, it records the trip data (see Table 5.5 in Design Concepts Section), and changes its activity state to tied up in port, where it remains until the start of the next simulation day, when it begins the cycle again.

At the beginning of each day External vessels are created on fishing grounds. External vessels do not decide where to fish initially, they are distributed across grounds according to a probability value based on previous patterns in effort from the VMS data. External vessels fish for 2 hours and evaluate where to fish next, 50% of the time moving to the neighbouring cell with the highest catch rate, and 50% of the time moving at random. The External vessels extract scallop biomass, and the cell biomass is depleted accordingly, but the activity and catches of individuals are not recorded. The external vessel processes are more deterministic, so as to simulate the scallop biomass removed by external vessels, but not to predict the behaviour and responses of these vessels as such. External vessels recorded 5969 logbook records in the reference period 2011-2013, giving an average of 1989 trips per season (Chapter 3). External vessels are therefore programmed to fish in cells with a probability according to this previous effort so that approximately 1989 trips are taken in a season, spatially distributed according to the previous distribution of effort.

At the start of each simulation day, the model evaluates if the total scallop catch so far has exceeded the total allowable catch model regulation. If it has, the model stops, and no more fishing takes place.

5.4. Design Concepts

Basic Principles

The model is based on human decision-making theory and the behavioural ecology theory of optimal foraging (Begossi, 1992; Lee *et al.*, 2014; MacArthur and Pianka, 1966); individuals generally operate in a way that either directly, or indirectly, maximises their net money intake over time. The marginal value and central place foraging theories provide the basis for behaviours, such that vessels fish in areas that will indirectly maximise their profits (Charnov, 1976; MacArthur and Pianka, 1966; Orians and Pearson, 1979). These decisions are however bound by conditions that ensure their behaviour is realistic (such as a maximum distance they can travel from port), with values derived from questionnaire surveys (Chapter 2).

Emergence

Vessel catches and profit, and the spatial distribution of fishing effort emerge from the model. The patterns emerge from the vessels' behavioural rules used to indirectly maximise their profits.

Adaptation

Vessels select patches via behavioural rules that, to varying degrees, indirectly maximise their return rate. Vessels are not able to adapt to their experiences by changing the rules that they follow to make decisions; i.e. if the model is set so that vessels select a patch at random, they will follow this behaviour throughout the model simulation. Vessels can, however, adapt to the catch rate they have received in a patch, by deciding to remain on that patch, or moving to another patch. The number of trips a vessel makes is imposed to reproduce observed patterns of possible or available fishing days, and are not modelled as adaptive decisions.

Objectives

Vessels only have a true objective when using the patch choice rules that require them to select the cell with the greatest difference between expected catch and expected cost. Here, the objective of vessels is to maximise their money intake over time by catching as many scallops as possible using as little fuel/money/time in doing so, through minimising the ratio between expected catch rates and travel costs. In the majority of behavioural settings, vessels are indirectly trying to maximise their money intake, by selecting patches that are above a certain threshold, such as the minimum viable catch rate, or have the highest catch rate, but it is the model user who has defined this.

Learning

Vessels do not demonstrate learning in this model, rather they continue to use the same decision rules throughout.

Prediction

Vessels will predict the catch rate that they are going to receive in a cell, which assumes that vessels know the scallop biomass in each cell. Vessels do not necessarily receive the catch rate that they expect to receive from a cell (to simulate small scale variation in catch rates). As it is a small fishery with a relatively stationary resource, it is appropriate to allow vessels to sense catch rates over the whole model world. However, they only select a patch to fish in that is within a realistic distance threshold as identified in the questionnaire surveys (Chapter 2).

Sensing

Once fishing, vessels can sense the catch rates in the current and neighbouring patches to decide whether to move to another patch. They can also sense the catch rates across the whole model world when calculating if a patch has an above average catch rate.

Interaction

Vessels are indirectly competing for scallops in the model; whilst they do not directly compete, if one vessel removes scallops from a patch, these scallops are no longer available for the other vessels. There is no direct interaction between vessels, as during questionnaires fishermen stated they would tow very close to another vessel, so there is no interference competition. They also said they would discuss where there are good catch rates with other fishers, but rarely took this information into account when deciding where to fish, therefore there are no interactions related to social communication in the model.

Stochasticity

In patch selection behaviour, if multiple cells offer equally good catch rates, or 'qualify' as potential patches, then one is chosen at random, introducing some spatial stochasticity. In addition, a vessel will not necessarily receive the expected catch rate; the received catch rate will be drawn from a random distribution with a mean of the expected catch rate, and a standard deviation of 10% of the expected catch rate. This is to simulate small scale variation in catch rates within a patch. Nevertheless, this model has relatively little stochasticity.

Collectives

There are no collectives (e.g. a social group) in the model currently.

Observation

Each time a vessel completes a fishing trip, model logbook data are recorded (Table 5.5). Spatial information is also provided by the models animation, and in values recorded by the fishing patches (grid cells) themselves.

Table 5.5. Variables written to an output file at the end of a fishing trip, to mimic logbook records.

Variable	Description
Date	The day the trip took place on
Month	The month in which the trip took place
Who	Which agent is recording the trip
VCU	The size of the vessel
Strategy	The strategy category of the vessel
MyPort	The port the vessel operates from
TripNumber	The trip number (i.e. trip ID per vessel)
TimeSteaming	The time the vessel spent steaming
TimeTowing	The time the vessel spent towing
SteamSpeed	The vessels steaming speed, to calculate fuel costs
TowSpeed	The vessels towing speed, to calculate fuel costs
FuelUsed	The total amount of fuel used
TripDuration	The total trip duration (i.e. time spent at sea)
FishHours	The total time spent towing
HoldStatus	The hold status (i.e. kg of scallops on the vessel) at the end of the trip
PatchDist	The distance the vessel travelled from port
Patch-choice-decision	The set of patch choice behavioural rules being followed
Between-patch-decision	The set of between patch decision behavioural rules being followed
Return-decision	The set of return to port behavioural rules being followed
Visited-patches	A list of the visited-patches

5.5. Initialisation

At the beginning of the simulation 26 fishing vessels are created. There are 3 different types of Manx vessel: quality maximisers (QLM), quantity maximisers (QTM), and efficient fishers (EFF) as determined from a questionnaire survey (Shepperson *et al.*, 2016).

The number of vessels of each type, in each port, was determined from logbook data. From the logbook records, the proportion of trips that took place from Douglas, Peel, Port St Mary, and Ramsey were 23%, 38%, 23%, and 17% respectively; the proportion of vessels in each strategy QLM, QTM, and EFF was 29%, 21% and 50% respectively, but the proportion of trips made by vessels in each strategy was 21%, 20%, and 60% respectively.

An average of 1634 trips were made by Manx vessels per season, equating to an average of 343 trips by QLM vessels, 327 vessels by QTM vessels, and 980 trips by EFF vessels per season. The model was initialised with 26 vessels, 8 QLM, 5 QTM, and 13 EFF. The model season is 210 days in length, so to make 343 trips the QLM vessels were attributed with a 20% probability of fishing each day, QTM a 31% probability of fishing, and EFF a 36% probability of fishing each day. The vessels in each strategy

were distributed between the ports according to the proportion of trips made at each port by each strategy in the logbook records (Table 5.6).

The model structure is also set at initialisation, determining the behavioural rules that vessels will use to select fishing patches and decide when to return to port throughout the simulation (see Submodels section). Each vessel is attributed with its state variables accordingly (Table 5.7).

Table 5.6. The proportion of trips made from each port by each strategy.

	QLM		QTM		EFF	
	%	No. in model	%	No. in model	%	No. in model
Douglas	0.16	1	0.33	2	0.10	1
Peel	0.67	5	0.35	2	0.52	7
Port St Mary	0.04	0	0.14	1	0.29	4
Ramsey	0.13	1	0.18	1	0.09	1

Table 5.7. Initialisation values for each type of vessel in the model

Category	Variable	Strategies			Unit
		QTM	QLM	EFF	
Physical Variables	VCU	M = 215 SD = 21.5	M = 129 SD = 12.9	M = 147 SD = 14.7	
	NumberOfDredges	= 0.019 (vcu) + 2.984			Number of dredges towed
	DistancePerTick	(18kmph / 60) * 4) = km per tick = 1.2 1 unit of distance in model = 3km Distancepertick = 0.4 units	((14kmph / 60) * 4) = km per tick = 0.93 1 unit of distance in model = 3km Distancepertick = 0.31 units	((14kmph / 60) * 4) = km per tick = 0.93 1 unit of distance in model = 3km Distancepertick = 0.31 units	
	HoldingCapacity	9006	4085	8512	tons
Financial Variables	FuelPerSteamHour	= 0.142 (vcu) + 4.358	= 0.142 (vcu) + 4.358	= 0.142 (vcu) + 4.358	Litres per hour
	FuelPerTowHour	= 0.146 (vcu) − 0.808	= 0.146 (vcu) − 0.808	= 0.146 (vcu) − 0.808	Litres per hour
	GrossTarget	1167	567	846	£
	GoodGross	2083	1083	1393	£
	SeaStateTolerance	6	6	6	Beaufort
Behavioural Variables	TowSpeed	4.4	4.4	4.4	kmph
	MaxDuration	51	46	40	hours
	MaxFishHours	13.7	14	15.7	Hours
	HandlingTime	25.8	13.6	15.1	Minutes
	MaxDistance	88.0	32.4	79.1	Km
	NormalDeptDist	29.1	12.6	13.3	Km
	GivingUpRate	7.44	9.71	5.78	Kg per dredge per hour
	PoorTolerance	2	3	2	Tows
	LikelihoodOfFishing	0.31	0.20	0.36	percent
Activity during simulation	CurrentActivity	0	0	0	
	TripNumber	0	0	0	
	HoldStatus	0	0	0	
	DistanceToPort	0	0	0	
	ChosenGround	NA	NA	NA	
	ReceivedCpue	NA	NA	NA	
	TimeSteaming	0	0	0	
	TimeTowing	0	0	0	
	Visited-patches	NA	NA	NA	
	TripDuration	0	0	0	
	FishHours	0	0	0	

5.6. Input Data

Each April a scallop survey and stock assessment quantifies the scallop biomass recorded at survey points around the Isle of Man (Figure 5.2). This biomass was interpolated to give a raster layer of scallop biomass distribution according to the survey. Three starting biomass values were used: 5000, 6000, and 7000 tons; 6000 tons was decided to be a reasonable estimate based on expert opinion, and using a value either side of this accounts for the uncertainty in this estimate. This biomass was then distributed across the model environment proportionally, according to the survey data for scallop densities. The survey has relatively low replication, therefore the values were scaled according to the previous trends in effort, to attribute cells with an expected catch rate based on both previous catches and on the survey data. To prevent scallops being attributed to areas where they would unlikely be found (e.g. due to substrate type), cells in which no fishing had taken place in the 2011-2013 reference period were attributed with an expected catch rate of zero.
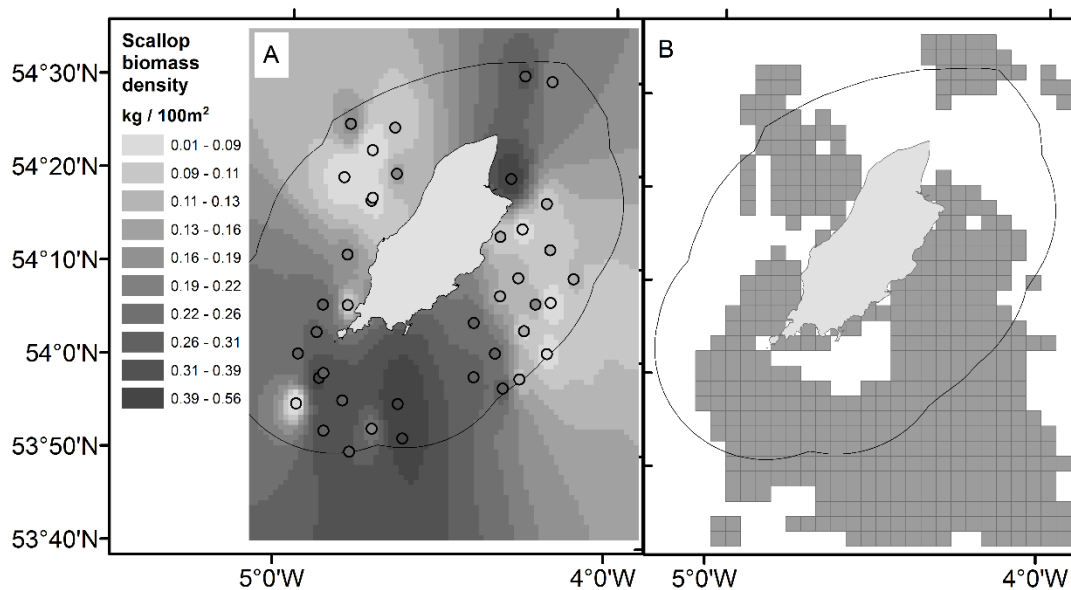
Figure 5.2. A) Interpolated scallop survey biomass data, and the survey locations. Survey locations are selected based on habitat parameters and track records of fishing activity from vessel monitoring system data. B) The extent of fishing activity, which makes up the possible fishing patches in which fishing activity is permitted in the model.

5.7. Submodels

5.7.1. Activity State: In Port

At the beginning of each day (i.e. Time = 0), a vessel determines if it will go fishing that day. It does this by evaluating a random number (0-1) against the likelihood that it will head to sea on a given day, according to the proportion of days fished by its vessel type in logbook data. If the vessel does not head to sea, it remains in the 'In Port' activity state until the following day.

If the vessel heads to sea, it increments its trip number by 1, and resets its trip variables to zero (time spent steaming, time spent towing, trip duration, time on a patch, and hold status). The vessel then chooses the patch that it will first target, according to one of eight submodels for patch choice which can be selected using a selector button on the model interface (Table 5.8). The patch choice model is a global setting, i.e. in any simulation all fishers will use the same behavioural rule throughout. A fishers uses the selected behavioural rule to select its target patch from a limited set of possible patches. A vessel can only choose between patches that have had some fishing within the past 3 year reference period, are within the 12nm Sea, are not a closed area, and are within the maximum possible distance that they can travel. The patch must not be port, and must be more than 0 distance from port. Once a vessel has chosen its target patch, it sets its heading towards the patch, and calculates the distance from its home port to the patch according to a cost distance raster that accounts for the increased travel time of navigating around land.

Table 5.8. Possible patch choice decision settings that can be used in the model

Patch Choice Model	Description	Model Type (how it relates to foraging theory)
1. Random Patch Choice (null model)	Vessels select a patch at random.	Null model
2. Highest Expected Catch Rate	Vessels select the patch which has the highest expected catch rate.	Optimal Patch
3. Threshold catch rate (average catch rate of all patches)	Vessels select a random patch that has a scallop biomass above the average biomass of all patches.	Marginal Value Theorem (Charnov, 1976)
4. Threshold catch rate (the giving up rate)	Vessels select a random patch that has an expected catch rate above their own 'giving up' threshold catch rate, below which they consider it is no longer viable to fish.	Marginal Value Theorem (Charnov, 1976)
5. Catch Cost Ratio	Vessels select the patch that has the greatest ratio between expected catch, and the cost of steaming to the patch and back.	Central Place Foraging Theorem (Orians and Pearson, 1979)
6. Conjoint Analysis	Vessels select the patch which has the highest utility score, according to a conjoint analysis of patch choice decisions (only distance and catch currently)	Utility Model (Shepperson *et al.*, 2016)
7. Previous Effort	Vessels select a patch which has shown above average trend in effort in the observed data (2008-2013)	
8. Above a threshold conjoint utility	Vessels select a patch that has an above average conjoint utility	Utility Model (Shepperson *et al.*, 2016)

5.7.2. Activity State: Steaming to a Patch

A vessel evaluates if the straight line distance from its port to the chosen patch is less than the 'real' distance to the patch determined from the cost distance raster. If the straight line distance is less than the 'real' distance, it means taking a straight line route would take the vessel over land. Therefore, the vessel calculates an adjusted 'distance per tick' so that it still steams in a straight line in the model, but it steams more slowly to account for the time it would have taken to travel around the land.

During each tick, the vessel increments its variable 'time steaming' by 1, and evaluates if it has reached the chosen patch. If it has reached the chosen patch, it sets the 'time on patch' and 'time towing' variables to zero, and changes its current activity status to 'towing'.

5.7.3. Activity State: Towing

A vessel remains on the patch in the towing activity state until the 'tow duration' and 'handling time' periods have passed. During each tick, the vessel increments its 'time towing' and 'time on patch' variables by 1. Once the tow is complete (i.e. time on patch > tow duration + handling time), the vessel increments the patch tow count by 1, resets their 'time on patch' variable to zero, and performs the 'catch-deplete' procedure to determine how much they have caught, and to update the scallop biomass in the cell accordingly. They then either decide which should be the next patch they target, or whether they should return to port.

To perform the 'catch-deplete' procedure, vessels calculate the catch they have received, add it to their hold, and subtract it from the scallop biomass within that cell. To calculate how much they have caught they use the following equations:

(1) Tow distance = ((tow speed x 1000) / 60) x tow duration

   where tow speed is in kmph, and therefore requires converting to metres per minute, and tow duration is in minutes.

(2) Area swept = 0.75 x tow distance x number of dredges

   where the width of a single dredge is 0.75m

(3) Expected catch = area swept x biomass per m^2 x 0.33

   where the gear efficiency was estimated as 33% (Beukers-Stewart, 2001)

(4) Received catch = drawn from random normal distribution, with a mean of the expected catch, and standard deviation of 10% of the expected catch.

To ensure no vessel receives a negative catch, if the received catch returns a value below zero, it is set as zero. The received catch biomass is then subtracted from the cell biomass, and the biomass per m^2 is updated accordingly.

Once a fishing event is complete the vessel decides if it should return to port. If their hold status is either above their individual daily limit or above their hold capacity, they reduce their hold status to the limit value, and change their activity status to returning to port. Aside from these restrictions, there are 4 possible return to port decision (Table 5.9)

Table 5.9. Possible return to port decision settings

Return to Port Model	Explanation
1. At curfew	A vessel will fish for as long as it is allowed.
2. Maximum fishing time	A vessel will return to port before the curfew if it reaches its own limit for fishing time first.
3. Minimum viable gross	If a vessel's hold status exceeds what it considers as a minimum viable gross, it will return to port. It will return at curfew if not before.
4. 'Good' takings	A vessel will return to port before the curfew if its hold status exceeds what it considers as good takings.

After completing a fishing event, if a vessel is to remain at sea, it will decide whether to remain towing on the same patch, or to move to a new patch, using one of six rules (Table 5.10).

Table 5.10. Possible between patch decision settings

Next Patch Model	Explanation
1. Random	Vessel selects next patch at random from the current patch and its 8 neighbours.
2. Highest Rate	Vessel selects the patch with the highest expected catch rate, from its current patch and its 8 neighbours.
3. 50:50 random:highest	50% of the time the vessel selects a patch at random, and 50% of the time it selects the patch with the highest catch rate.
4. MVT (average)	If the current patch has a catch rate above the average of the 8 neighbouring patches, it remains on that patch. If not, it selects a neighbouring patch with an above average catch rate.
5. MVT (givingup)	If the current patch has a catch rate above its giving up rate, it remains on that patch. If not, it selects a neighbouring patch with a catch rate above its giving up rate. If there are no patches above its giving up rate, the vessel returns to port.
6. Optimisation	A vessel will select the patch which has the greatest ratio between catch rate and travel cost to return to port.

5.7.4. Activity State: Moving Between Patches

If a vessel is in the 'moving between patches' activity state, during each tick it will increment its time steaming variable by 1. It will evaluate if the patch it is on is the patch it is aiming for: if so, it will change its activity state to towing, and set its time on the patch to zero; if not, it will move forward one unit, and remain in the moving between patches activity state.

5.7.5. Activity State: Returning to Port

Vessels in the 'returning' activity state are travelling back to port. During each tick, a vessel faces port, and travels forward 1 unit, and increments its time steaming variable by 1. After travelling forward 1 unit, the vessel evaluates if the current patch is port: if so, it performs the 'arrive at port' set of commands; if not, it remains in the 'returning' activity state.

When a vessel arrives at port, it submits a logbook record, and updates the relevant variables. The hold status (scallop biomass) is added to the total catch variable. The time spent towing and steaming during this trip are added to the variables for total time towing and total time steaming. The total time at sea is calculated by adding the total steaming and total towing times. The total fuel cost is calculated from each vessels fuel use rates per towing and steaming, with a fuel price of 0.65 per litre of fuel. The total catch value is calculated with an average market price of £1.42 per kg of scallops. The total profit is calculated by subtracting a third of the catch value as crew wages, and then subtracting the fuel cost from the remaining. The time in port, trip duration, and fishing hours are reset to zero, and the activity state is set to 'in port'.

5.8. References

Begossi, A. 1992. The use of optimal foraging theory in the understanding of fishing strategies: A case from Sepetiba Bay (Rio de Janeiro State, Brazil). Human Ecology, 20: 463–475.

Begossi, A., Clauzet, M., Hanazaki, N., Lopes, P. F., and Ramires, M. 2009. Fishers' decision making, optimal foraging and management. *In* III Seminario de Gestao Socioambiental para o Desenvolvimento Sustentavel da Aquicultura e da Pesca no Brasil - III SEGAP 2009, pp. 1–5.

Beukers-Stewart, B. D. 2001. The efficiency and selectivity of spring toothes scallop dredges, a comparison of direct and indirect methods of assessment. Journal of Shellfish Research, 20: 121–126.

Charnov, E. L. 1976. Optimal Foraging, the Marginal Value Theorem. Theoretical Population Ecology, 9: 129–136.

de Oliveira, L. E. C., and Begossi, A. 2011. Last Trip Return Rate Influence Patch Choice Decisions of Small-Scale Shrimp Trawlers: Optimal Foraging in São Francisco, Coastal Brazil. Human Ecology, 39: 323–332.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES Journal of Marine Science, 60: 371–380.

Evans, M. R. 2012. Modelling ecological systems in a changing world. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 181–190.

Fulton, E. a, Smith, A. D. M., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Grimm, V., and Railsback, S. F. 2005. Individual-Based Modeling and Ecology. Princeton University Press, Princeton.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., *et al.* 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 198: 115–126.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., and Railsback, S. F. 2010. The ODD protocol: A review and first update. Ecological Modelling, 221: 2760–2768.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., *et al.* 2004. When can marine reserves improve fisheries management? Ocean & Coastal Management, 47:

197–205.

Lambert, G. I., Jennings, S., Hiddink, J. G., Hintzen, N. T., Hinz, H., Kaiser, M. J., and Murray, L. G. 2012. Implications of using alternative methods of vessel monitoring system (VMS) data analysis to describe fishing activities and impacts. ICES Journal of Marine Science, 69: 682–693.

Lee, A. Van Der, Gillis, D. M., and Comeau, P. 2014. Comparative analysis of the spatial distribution of fishing effort contrasting ecological isodars and discrete choice models. Canadian Journal of Fisheries and Aquatic Sciences, 71: 141–150.

MacArthur, R. H., and Pianka, E. R. 1966. On Optimal Use of a Patchy Environment. The American Naturalist, 100: 603–609.

Orians, G. H., and Pearson, E. 1979. On the Theory of Central Place Foraging. *In* Analysis of Ecological Systems. Ed. by D. J. Honrs, G. R. Stairs, and R. D. Mitchell. Ohio State University, Columbus.

Pascoe, S., and Mardle, S. 2005. Anticipating fisher response to management: Can economics help? ICES Annual Science Conference. Aberdeen.

Shepperson, J., Murray, L. G., Mackinson, S., Bell, E., and Kaiser, M. J. 2016. Use of a choice-based survey approach to characterise fishing behaviour in a scallop fishery. Environmental Modelling & Software, 86: 116–130.

Sosis, R. 2002. Patch Choice Decisions among Ifaluk Fishers. American Anthropologist, 104: 583–598.

CHAPTER 6: Developing an Individual-based Model to Understand Fishers' Patch Choice Behaviour, using Pattern Oriented Modelling and Approximate Bayesian Computation

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6.1. Abstract

Human behaviour is an area of considerable uncertainty in fisheries management; failing to account for the behavioural response of fishermen can lead to unintended consequences of management. Individual-based models (IBMs) could help to address some of the knowledge gaps in our understanding of fisher behaviour, and help both managers and fishers better predict and understand the potential consequences of different management scenarios. Nevertheless, a lack of comprehensively validated fishery IBMs may have hindered their application in fisheries management. In particular, models are often built with little consideration given to alternative possible submodels of fishing behaviour. By contrasting alternative decision models, or 'theories' of behaviour, more robust models could be developed.

The primary objectives were to design an IBM of the Isle of Man scallop fishery, and then use it to develop and test different submodels, or theories, for patch choice behaviour by fishing vessels. Approximate Bayesian Computation was used to select for models that generated outputs closest to real fishery values in vessel monitoring system and logbook data.

Using simple foraging decision rules, parameterised using data collected directly from fishermen, it was possible to build an IBM that could reproduce patterns seen in the Isle of Man scallop fishery with reasonable similarity. The model was able to reproduce realistic values for the extent of fishing, average trip CPUE, average fishing hours per trip, average steaming hours per trip, average fuel used, average landings, and total landings across the fishing season. The development process increased our understanding of fishing behaviour in the Isle of Man scallop fishery, and provided insights into how to predict fishing behaviour in a model environment. In particular, it highlighted the importance of including a random component of fishing behaviour (e.g. to account for gut feeling), rather than using only fully informed behaviour.

Predicting responses to management by modelling fishers under the assumption that they act in an economically rational manner, or as optimal foragers, may overestimate the capacity of the fleet to compensate for restrictions such as closed areas, and may underestimate the economic impact that a management measure may have on the fishery.

6.2. Introduction

Human behaviour is an area of considerable uncertainty in fisheries management (Fulton *et al.*, 2011). Failing to account for the behavioural response of fishermen to management can lead to unintended consequences of management, and even produce negative environmental, economic, or social effects (Hilborn *et al.*, 2004; Pascoe and Mardle, 2005). An inability to foresee (or failure to consider) the displacement of effort following management can lead to unintended consequences (Dinmore *et al.*, 2003). To implement effective fisheries management we should be confident that fishers will respond to management actions as intended, but to do this we need a good understanding of fisher behaviour and how to predict it (Bacalso *et al.*, 2013; Charles, 1995; Gordon, 1953; Hallwass *et al.*, 2013; Hilborn, 2007; Marchal *et al.*, 2007; Murray *et al.*, 2011; Salas and Gaertner, 2004; Wilen *et al.*, 2002).

6.2.1. Individual-based modelling could be a good platform to better understand fishing activity

Individual-based models (IBMs) could help to address some of the knowledge gaps in our understanding of fisher behaviour, and allow us to create simulation tools that could help both managers and fishers better predict and understand the potential consequences of different management scenarios (Evans, 2012; Grimm and Railsback, 2005). IBMs view systems as having properties that arise from the behaviours and interactions of the individuals that make up the system (Grimm and Railsback, 2005). This makes it relevant for modelling fishing behaviour, as it is the decisions made by, and behaviours of, individual fishermen that drive the spatial patterns seen in the system (Plaganyi *et al.*, 2014; Hilborn, 2007).

With advances in computing power, IBMs present an opportunity to model complex systems with more realism than previously possible (van der Vaart *et al.*, 2015). Increasingly complex models can, however, be criticised as being 'black boxes', that are too complex to really understand and communicate (Topping *et al.*, 2010). The structure of a model is a compromise between realism, complexity, and efficiency (Evans, 2012; Evans *et al.*, 2013); an IBM must capture all of the processes and heterogeneity required to understand the system, but must also not be overly computationally demanding, or so complex that parameter uncertainty renders it too complex for application.

6.2.2. Open, simple, realistic model development

Optimal Foraging Theory (OFT) (MacArthur and Pianka, 1966) has been demonstrated as a suitable framework for investigating fisher behaviour (Begossi, 1992; Begossi *et al.*, 2009; de Oliveira and Begossi, 2011; Lee *et al.*, 2014; Sosis, 2002). OFT states that individuals aim to maximise their net energy intake over time (analogous to catches or profit for a fisher), and is therefore comparable to assuming fishers follow profit maximisation behaviour (Holland, 2008). Modelling fishers under the framework of OFT provides a relatively simple, established model of patch selection behaviours on which to base a model. Nevertheless, the questionnaire surveys (Chapter 2) and analysis of VMS and logbook data (Chapter 3) suggested that there may be violations to some of the assumptions of OFT; namely that all fishers do not have equal abilities, fishers may not have complete knowledge of catch rates in the system, and importantly, not all fishers may be true profit maximisers (Chapter 2, Chapter 3). An IBM provides a more flexible framework within which to account for deviations from such theory (Grimm and Railsback, 2005).

To parameterise an IBM, a detailed understanding of the behaviours in the system is required. Collecting data directly from fishers can be termed fishers knowledge (FK), and can provide useful and reliable information on a fishery system (O'Donnell *et al.*, 2012; Shepperson *et al.*, 2014, 2016; Teixeira *et al.*, 2013). Using data collected directly from fishers may help to make a model more realistic, for example providing boundary conditions such as a maximum distance a vessel is able or willing to travel. In addition, it may help to keep the model simpler, allowing redundant processes to be excluded, for example, fishers consistently stated they were able to fish very close to one another, therefore no displacement competition between vessels needed to be modelled (Chapter 3), whereas this has been shown to be important in other fishery systems (Rijnsdorp, 2000). Understanding more about fishing strategies through interviewing fishers also highlighted a potential need to include individual variability in capabilities and objectives / requirements, and suggested some fishers may not be true profit maximisers (Chapter 2).

6.2.3. Pattern Oriented Modelling In IBMs

IBMs are often developed using pattern oriented modelling (POM), which is essentially a protocol to build and evaluate IBMs (Grimm *et al.*, 2005; Grimm and Railsback, 2012). The first stage of POM uses patterns in the real system to determine the entities and processes needed in the model; the second stage of POM considers how to find realistic representations of these processes, using alternative submodels of different complexity or structure to represent each process (Grimm and

Railsback, 2012). Multiple patterns observed in the real system are used to guide model development and evaluation; models are then accepted or rejected based on their ability to reproduce these patterns (e.g. Railsback and Johnson, 2011). If a model can reproduce multiple patterns seen in the real system then it can be assumed that it is realistically recreating some of the internal processes in the system (Grimm *et al.*, 2005). Both strong and weak patterns should be considered (Grimm and Railsback, 2012). Strong patterns often need describing by data or equations, whereas weak patterns are often more qualitative. A strong pattern is something pronounced, for example in a fishery this might be spatial patterns in effort; recreating these could be a good indicator that you have captured the system well. Nevertheless, weak patterns (e.g. fishers preferring one ground over another) are less pronounced, and may be reproducible by multiple mechanisms in a model, but if a model can reproduce multiple weak patterns it can be a strong indicator that structural realism has been achieved (Grimm and Railsback, 2012).

6.2.4. Approximate Bayesian Computation provides an objective structured way to assess model performance.

POM can be criticised as being relatively qualitative, and some argue that for individual-based modelling to become more mainstream in statistical modelling and prediction, a more quantitative statistically rigorous validation process is needed (van der Vaart *et al.*, 2015). Approximate Bayesian Computation (ABC) is a Bayesian technique that can be used to evaluate IBM performance, and to perform parameter estimation and model selection (van der Vaart *et al.*, 2015). In ABC, the data generated from model simulations are reduced to summary statistics, and then simulations that generate values closest to the real observations are retained as the best models (Csillery *et al.*, 2010). The subsample of accepted models can then be used to explore parameter uncertainty, for parameter calibration, to identify parameters of lower importance, and to select between different model structures (e.g. a complex model vs a simpler model with fewer parameters) (Csillery *et al.*, 2010; van der Vaart *et al.*, 2015). This complements POM, as it provides a more objective and systematic method of assessing the performance of different model structures and parameters.

6.2.5. Using IBM and ABC could allow us to better understand how to predict fishing activity.

Validation of fisheries IBMs has previously been somewhat qualitative, or based on relatively few coarse scale data points (e.g. Dowling *et al.*, 2012; Little *et al.*, 2009), perhaps due to the paucity of

appropriate data for validation. In addition, IBMs are often constructed using only one model of decision making, with little consideration presented of alternative processes or mechanisms (Grimm *et al.*, 2005). The lack of comprehensively validated IBMs may hinder their application in fisheries management, through a lack of evidence that models can accurately predicting fishing activity and responses to novel management scenarios. By contrasting alternative decision models, or 'theories' of behaviour (Grimm and Railsback, 2005), a more rigorous approach to model development could be achieved. ABC could help to build and evaluate an IBM of fishing behaviour through providing an objective assessment of which fishing behaviours provide the most realistic model. Comparing different submodels of the same system (e.g. different behavioural rules for how to decide where to fish) could increase confidence that not only the outputs of the model are realistic, but that the underlying processes driving the patterns are realistic (Grimm and Railsback, 2012). Alternative behavioural models should be systematically tested to build more robust models (van Putten *et al.*, 2012).

Nevertheless, there can be multiple potential explanatory models of a system (Csillery *et al.*, 2010); model selection does not necessarily imply selecting a single 'best' model (Ripley, 2004), as different mechanisms in a model could lead to the same emergent patterns (Csillery *et al.*, 2010). There could, therefore, be several equally good candidate models to describe patterns seen in a fishery system. An IBM provides a virtual laboratory to compare different behavioural submodels (e.g. patch choice decision rules), evaluating fisher foraging theory in a more complex and realistic environment than most mathematical models, whilst still being fully controllable with measureable outputs. Model validation often has two steps; a model output verification process in which model outputs are compared to the data used to create them, and a model corroboration process, in which model outputs are compared against an independent dataset not used at all during the model development and verification stages (Grimm *et al.*, 2014; Augusiak *et al.,* 2014). In this Chapter a model output verification is presented, during which the model is 'tweaked' to improve its performance in relation to the real fishery data. Documenting this development and validation process has the benefit of increasing transparency, documenting what mechanisms were included and/or rejected, and indicating the importance of different processes (Grimm *et al.*, 2005; Grimm *et al.*, 2014).

6.2.6. Aims and Objectives

The primary objectives were to design an IBM of the Isle of Man scallop fishery, and then use it to develop and test different submodels or theories for patch choice behaviour by fishing vessels. The model design and development followed the 'pattern-oriented modelling' strategy (Grimm *et al.*,

2005; Grimm and Railsback, 2012), in which characteristic patterns observed in the real fishery, relevant to the model's purpose, were used as the basis for designing and testing the model. ABC was employed to provide an objective analysis of which submodels best recreated the values and patterns seen in the real fishery. The specific aims were to: 1) develop an IBM of scallop fishing activity in the Isle of Man, with the functionality to test out multiple behavioural submodels (i.e. different ways that fishers can make decisions regarding where to fish); 2) determine which behavioural submodels best recreated the Isle of Man scallop fishery; and finally 3) to draw conclusions relevant to predicting fishermen's foraging behaviour in a behavioural model.

6.3. Methods

6.3.1. The Isle of Man Scallop Fishery

The Isle of Man provides an ideal candidate system to develop a model of fishing behaviour as it is a simple and data-rich system. Vessels mainly complete single day trips in a relatively confined area, indirectly competing for, and depleting, a stationary, patchy resource (Chapter 3). In addition, all vessels fishing for scallops in the Isle of Man territorial sea are required to carry a mandatory satellite tracking device, called a vessel monitoring system (VMS), which provides approximately two-hourly spatial position data on the vessel. Vessels are also required to return daily logbook records of their catches. By joining the VMS position records with the logbook catch data, the resulting spatially resolved catch data can be used for scientific research into fishing activity (Lambert *et al.*, 2012; Lee *et al.*, 2010), and as a dataset against which an IBM can be comprehensively validated. A stock survey is also completed yearly, with scallop biomass recorded at around 30 locations in the 12nm Sea (Bloor and Kaiser, 2016). This data-rich simplicity makes it an ideal system to develop and validate an IBM, and to test different submodels or theories for modelling fishing behaviour, to inform future model development in more complex fisheries.

King scallops (*Pecten maximus*) and Queen scallops (*Aequipecten opercularis)* have been important fisheries for the Isle of Man since the 1950s, and form the most valuable fishery for Manx (Isle of Man) vessels (Hanley *et al.*, 2013). This model focussed on the behaviour of scallop dredgers when targeting the more valuable king scallop fishery. King scallops (hereafter referred to as 'scallops') are fished using toothed Newhaven dredges, which are each approximately 75cm in width, with eight 110mm metal teeth along the front edge of the dredge. The dredge teeth rake up scallops from the seabed, which are collected in a mesh bag behind the tooth bar. Groups of dredges are positioned along a tow bar which has wheels to hold the bar at a fixed altitude relative to the seabed and to reduce drag. In Manx territorial waters, scallop dredgers are restricted to using ten dredges within 3nm from shore, and 14 dredges in a zone from 3 to 12nm from shore. There is as curfew such that fishing is only permitted between 06:00 and 20:00, and a minimum landing size of 110mm. Vessels must hold a licence to fishing in the Manx territorial Sea, and the fishery is sometimes managed using area closures.

6.3.2. Characteristic patterns of the Isle of Man scallop fishery for model development

The first phase in pattern-oriented modelling is to identify a set of observed patterns that characterise the system's behaviour in relation to the problem to be modelled (Grimm *et al.*, 2005; Grimm and Railsback, 2012; Railsback and Johnson, 2011). These characteristic patterns observed in the real system tell us about the structure needed for a model of the system (e.g. the scale of the model, and what entities and processes are needed in the model). The patterns used should be general and robust, but are not always quantitative. Both strong quantitative and weaker qualitative patterns can be used in POM; recreating multiple weak patterns can provide strong support for a model (Grimm and Railsback, 2012). For the Isle of Man scallop fishery, the following patterns characterise fishing effort and catches, at the spatial and temporal resolution of interest (Chapter 3).

Pattern 1: Vessels operated predominantly daily fishing trips, steaming out to a patch at the start of a day and then fishing within a relatively small area throughout that day.

Pattern 2: The majority of fishing effort took place within the 12nm Sea, over known fishing grounds, (because scallops are relatively sedentary animals which form 'beds' or aggregations over suitable habitats). Vessels did not all fish in all available patches equally; they tended to fish at the grounds closest to their port.

Pattern 3: The fishing footprint increased as the season progressed, i.e. at the start of the fishing season, activity was more spatially clustered in smaller areas.

Pattern 4: The highest number of trips took place over the ground called 'East Douglas', but the highest total landings came from the ground called 'Chickens'. Non-Manx vessels showed less preference to the fishing ground called 'Targets' than Manx vessels.

Pattern 5: Vessels may follow different fishing strategies, and not all may be true profit maximisers (Shepperson et al., 2016, Chapter 2)

Pattern 6: Catch rates and landings declined throughout the season.

Pattern 7: There was individual variation in catch rates, landings, and spatial distribution of effort.

These patterns informed the model development. For example, vessels completed daily fishing trips, so a daily timestep was the lowest resolution at which the model could be run, and model processes were needed that led vessels to return to port at the end of the day. There is a curfew that prohibits vessels from fishing for more than 14 hours per day (08:00 – 20:00), so vessels in the model must be prohibited from fishing for longer than this. Nevertheless, there may be other processes that

contribute to the duration of trips within the curfew, such as gross targeting behaviour (Salas and Gaertner, 2004; Simon, 1955), which could also be tested. The spatial extent of the model focussed on the 12nm territorial sea, because this was where the majority of trips took place, and also the area for which complete data was available for model validation. Within the 12nm Sea, the most prosecuted ground was not the ground with the highest landings, which suggested that vessels needed to be able to choose where to fish not only based on expected catch rates. There needed to be different sized vessels, and processes that allowed individual variation in characteristics and catches that also allowed vessels to not necessarily act as true profit maximisers. Once fishing, vessels did not move far during a trip, so vessels in the model only evaluated nearby patches when deciding if/when to move patches, and were prevented from switching to a patch on the other side of the island mid-trip.

6.3.3. A Brief Model Description (See Chapter 5 for full description)

The purpose of the model is ultimately to explore the potential impact of different management measures on the Isle of Man scallop fishery from an environmental and economic perspective, in terms of the footprint of fishing and the reduction in catches for fishing vessels. In particular, it is designed to understand how the spatial extent and arrangement of closed areas affects the fishers' landings and costs and the amount/proportion of the scallop biomass removed in a season. For example, if we close an area to scallop dredging, where would fishers go instead (displacement of effort) to compensate for this lost area, what would the environmental impacts of this shift be, and would the fishers still be able to make enough money?

Initially, however, the model is used to understand more about predicting fishing activity, evaluating different submodels of fishing behaviours. There are four main decisions that fishers make in the model: 1) If they should fish that day; 2) where they should steam to at the start of a day to begin fishing; 3) after completing a tow, should they remain on that patch or move to a new location; and 4) when should they return to port. These decisions can be made in different ways; the first stage of model development is to determine what behavioural rules best recreate the fishery. For example, if fishers select a patch to fish based purely on the highest expected catch rate, is this more or less realistic than if they take account for the travel cost when deciding where to fish?

Briefly, the model consists of a fishery system divided into fishing 'patches' of 3km by 3km, which are each attributed with a scallop biomass and expected catch rate. At the start of each day in a model simulation, a fisher decides if it will fish that day, and if so, which fishing patch it should steam

out to. Once the vessel arrives on that patch it begins fishing. After completing a fishing event, the fisher evaluates whether it should remain fishing on that patch, or move to a different patch. At the end of the fishing trip the vessel returns to port and submits catch information that mimics logbook data from the real fishery. To validate the model, this catch information could be compared to VMS and logbook data from the real fishery, to see if values and trends observed in the real fishery were recreated in the model. Here we refer to a 'fisher' making a decision, which generally would refer to a skipper on a vessel with one or more other crew member(s), who form a single unit in the model. A full, standardised, model description was presented in Chapter 5.

6.3.4. Developing Hypotheses for Fisher Foraging Behaviour with an IBM

There are three behavioural decisions in this model that could influence the spatial distribution of fishing effort: the decision of which patch to steam out to at the beginning of a fishing trip, the decision of if, when, and where to move to after towing on a patch, and the decision of when to stop fishing and return to port. These form three independent decision processes in the model. There are also several different submodels, or behavioural settings, for each of these decision processes (i.e. different behavioural rules that vessels could follow) (Table 6.1). These different behavioural submodels were tested to determine the most realistic combination of behaviours for the 3 decisions. The models were run at three different starting biomass values (5000, 6000, 7000 tons), to account for uncertainty in this value, as it was derived from expert opinion.

Which behavioural rule, or submodel, a fisher uses is a 'global' model setting, which means that all fishers would follow the same behavioural rules during a simulation. There are 192 different combinations of behavioural rules, therefore 192 unique model structures that could be tested. Thus, a 'submodel' refers to a behavioural setting, e.g. choose a patch at random, return to port at curfew, and a 'model structure' refers to the overall combination of submodels used. Future model development could allow multiple behavioural rules within one simulation (i.e. some choosing where to fish at random, some choosing based on the highest expected catch rate), but in the initial model development, for simplicity, the different behavioural rules formed discrete submodels to select between. The behavioural rules tested in the model were related to optimal foraging theory and related models as described below in Table 6.2, and described graphically in Figure 6.1 and 6.2.

Table 6.1. Possible behavioural settings or submodels for the 3 decisions made in the model. There are 192 different combinations, therefore 192 unique model structures. See Table 2 for further description

	Patch Choice Decision	**Between Patch Decision**	**Return to Port Decision**
1	Random	Random	At curfew
2	Highest expected catch rate	Highest expected catch rate	After maximum possible fishing time
3	Above average expected catch rate	50% random, 50% highest expected catch rate	After a minimum threshold catch has been reached
4	Above a threshold expected catch rate	Above average expected catch rate	After a catch the fisher considers 'good' has been reached
5	The best ratio between expected catch and travel cost	Above a threshold expected catch rate	
6	Highest utility score	The best ratio between expected catch and travel cost	
7	Previous level of effort		
8	Above average utility score		

Table 6.2. Description of how the different behavioural submodels relate to foraging theory or a choice based conjoint analysis completed by the fishermen.

Category	Foraging Behaviour	Fisheries IBM
Random Behaviour	Foraging behaviour that is not guided by expected catch rates in any way. A forager moves randomly between foraging patches.	Pattern oriented theory development should include a 'null' theory as a baseline against which other alternative theories can be compared (Grimm and Railsback, 2012). The null model provides insights into the patterns that cannot be reproduced without some form of 'intelligent' or 'informed' patch choice behaviour. For example, in a null model, fishers would select which patch to fish in randomly, regardless of the expected catch rate in any patches. After towing in a patch, they would decide the next patch at random.
Optimal foraging theory	Foragers act in a way that maximises their net intake over time.	In some submodels fishers choose a patch with the highest expected catch rate; fishers have perfect knowledge of the model system, and always select the patch with the highest expected catch rates. A fisher would decide to leave a patch when an adjacent patch offers a higher expected catch rate.

Marginal Value Theorem	Foragers remain on a patch until the benefit of moving to a new patch exceeds the travel cost.	Some submodels resemble the marginal value theory of (Charnov, 1976). Fishers move to a new patch when they have depleted the resources at their current patch down to the average available throughout the whole system. A variant on this is that instead of assuming that fishers are aware of the average catch rates across the whole system, they select a patch and move between patches based on a 'giving up threshold' catch rate, below which the fisher considers it unviable to fish. In this submodel fishers move between patches when the current patch falls below the threshold value.
Central Place Foraging Theory:	The travel cost associated with a patch is weighed against the resource density.	Some submodels are related to central place foraging theory (Orians and Pearson, 1979). Fishers must travel from and return to a certain location at the end of each foraging trip, and therefore the 'expense' of the travel can be accounted for. For example, a fisher selects a patch which has the highest expected catch:travel cost ratio. After each tow, the fisher evaluates if any adjacent patches offer a better ratio between expected catch rates and cost of travel back to port.
Conjoint analysis:	This is not a foraging model, but because it currently only includes distance to port and expected catch rates, it somewhat resembles central place foraging theory, with the catch:cost ratio evaluated in a non-linear manner.	Two patch choice submodels are based on a questionnaire survey of fishermen in which they completed a choice experiment called a conjoint analysis (Shepperson *et al.*, 2016; Chapter 2). In this survey, fishers chose between virtual fishing patches attributed with variables such as sea state, distance to port, expected catch rates, meat yield, roe/gonad status, and rock content. Three fisher strategies, QTM, QLM and EFF were derived from differences in the way that fishers chose between these patches (Shepperson *et al.*, 2016). The full conjoint model could not be incorporated in the IBM due to data availability, but fishers can weigh up the distance travelled and the expected catch rates according to the conjoint utility score for each patch (which varies between the 3 strategies). This essentially assumes a constant meat yield (size of the white adductor muscle that we most commonly eat), roe/gonad status (reproductive status of the scallop, full gonads makes the scallop more valuable), and rock content (how much rock the dredges pick up, which is inconvenient and can damage dredges) across the model environment.
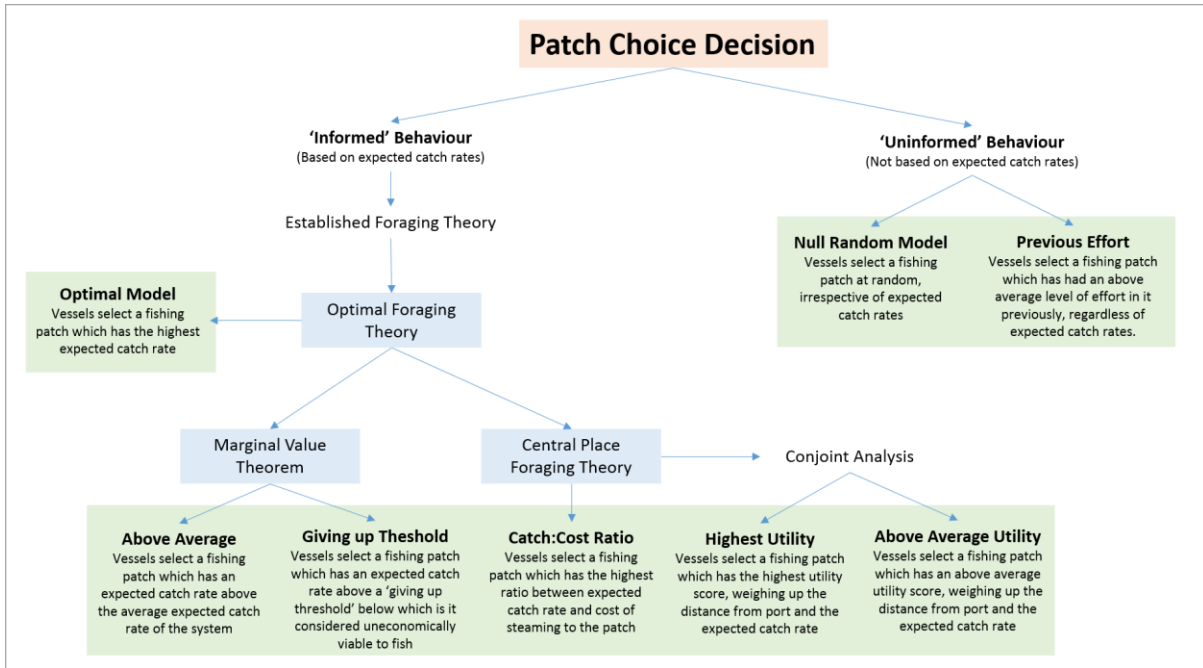
Figure 6.1. The different submodels for how a vessel decides where to fish, and how they relate to foraging theory. Previous effort is included in the 'uninformed' behaviour category as it relates to previous effort rather than directly assessing catch rates, although previous effort would likely have been influenced by catch rates. Green shading indicates a submodel / behavioural rule.
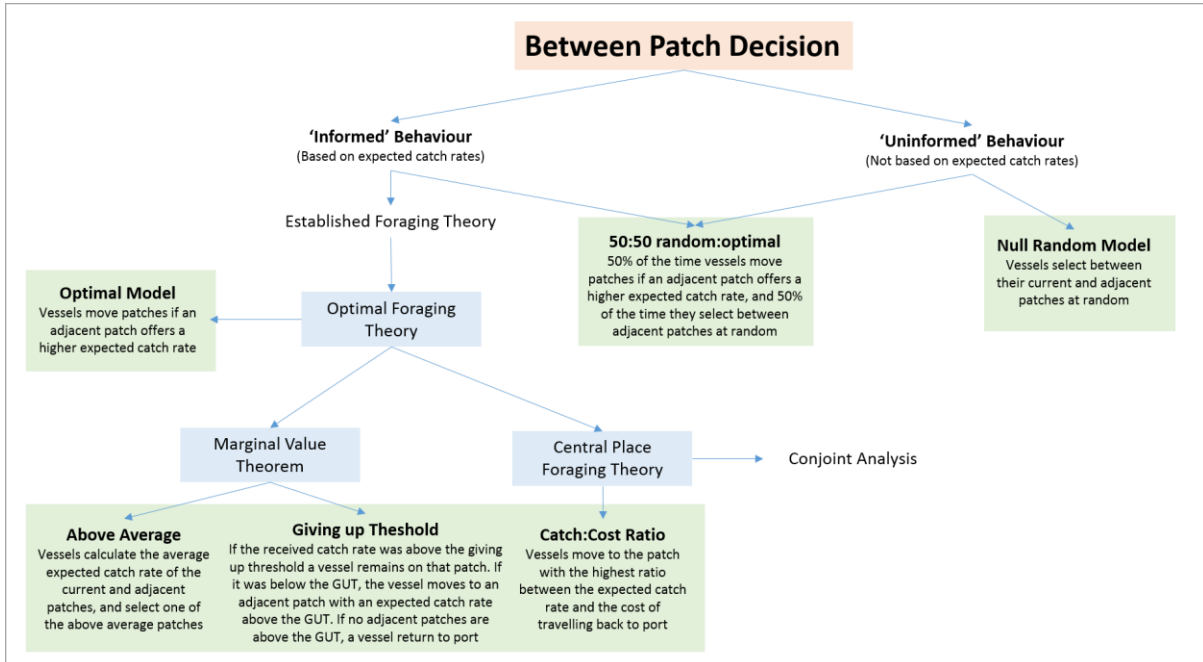
Figure 6.2. The different submodels for how a vessel decides when to change fishing patch, and how they relate to foraging theory. Green shading indicates a submodel / behavioural setting.

In all models, fishers could only choose from a set of 'possible patches' which met certain criteria specific to that individual. The patch had to be: within the maximum possible travel distance from port for that fisher; open to fishing; being within the 12nm territorial sea; and previously had experienced some fishing activity (i.e. it was a fishing ground).

The return to port decision submodels either demonstrated profit maximising or satisficing behaviour, with fishers choosing to return to port based on time restrictions or on catches:

1) Vessels return to port at curfew, fishing for the maximum time permitted.

2) Vessels return to port after the maximum time they are willing / able to fish for, based on questionnaire responses.

3) Vessels return to port once they have achieved catches they consider to reach a 'minimum viable gross'.

4) Vessels return to port once they have achieved catches they consider to be 'good takings'.

In all models fishers must return to port at curfew, regardless of which return to port decision rule they are using. Therefore the alternate decision rules can only shorten the fishing trip; e.g. a fisher may reach 'good takings' before the curfew, and so may return to port early, but may not remain fishing longer than curfew if 'good takings' has not been reached.

6.3.5. Comparing the model output to real-life patterns using ABC

Simulation experiments let us draw conclusions about which behavioural rules best represented the fishers' foraging behaviour, and best recreated the values and patterns seen in the real fishery. In ABC the data generated by the model are reduced to summary statistics, and then simulations that provide values closest to the real observations are retained as the best (Csillery *et al.*, 2010). This analysis uses the simplest version of ABC, rejection- ABC (Pritchard *et al.*, 1999). For model selection, a certain percentage of models with the smallest difference between the model output values and the real data values are retained; the ratio in which models are retained gives the relative probability that each model is correct (Csillery *et al.*, 2010). These best models can then be used to inform model development, to explore parameter uncertainty, for parameter calibration, and to identify parameters of lower importance (Csillery *et al.*, 2010; van der Vaart *et al.*, 2015). The ABC model selection used R code developed by van der Vaart *et al.,* (2015), which was based on the '*abc*' R package by Csillery *et al.,* (2010). The model selection followed the protocol described in Box 6.1, adapted from van der Vaart *et al.,* (2015). Parameters provided by fishermen during questionnaire

surveys were assumed to be realistic values (Chapter 2), so the models were not calibrated to provide more accurate values compared to the real fishery data.

ABC MODEL SELECTION

Step 1: Run each unique model 5 times at each of the three possible starting biomass values, resulting in 15 runs per model structure.

Step 2: Scale each data point in both the model outputs and the empirical data by dividing by the standard deviation of that data point in all model outputs. These data points relate to all of the monthly values presented in Figure 6.6, meaning the IBM is being fitted to all of the values and trends in the fishery simultaneously.

Step 3: Compute the distance 'ρ' between the scaled model outputs (m) and the scaled empirical data (D) according to Eq. 1:

$$\rho(m_i, D) = \sqrt{\sum_j \left(\frac{m_{i,j} - D_j}{sd(m_j)} \right)^2}$$ (Eq. 1)

where $m_{i,j}$ is run i's output for data point $_j$, D_j is the empirical data for data point $_j$, $sd(m_j)$ is the standard deviation of the model outputs for data point $_j$ in all model runs.

A scaling factor was used to normalise the scales of the data points, because, for example, total scallop catches were recorded in millions, whilst the extent was in hundreds. If these differences in scales of units were not appropriately scaled, the total catches would have an undue influence on the distance calculations simply because of the units used to measure them.

Step 4: Accept the top 1% of models, with the lowest distance between model output data and real fishery data.

Box 6.1. Model selection protocol, following methodology and code developed by van der Vaart et al., (2015), which was based on the 'abc' R package by Csillery et al., (2010).

6.3.6. The Stages of ABC and Model Validation

There were three stages to the model validation (Box 6.2). The results section is structured such that the reader is walked through these stages of model validation, guided by the lessons learnt at each stage. At each stage, the model output is compared to the real fishery values, and new hypotheses formed to test in the model; e.g. following output from Stage 1, a hypothesis arose whether increasing the randomness in patch choice behaviour may improve the model fit. There were two

aspects to comparing the model outputs: trends and magnitudes. For a variable, if the trend was captured well, but the magnitude was wrong, this could be corrected by calibration of parameters. If the trend was poorly captured, this may suggest that the structure of the model could be improved.

THE MODEL SELECTION PROCESS

Stage 1: Run the initial model using all possible behavioural structures (192 unique model structures, at 3 starting biomass values)

Stage 2: Run the model where vessels used an informed 'patch choice decision' 50% of the time, and a random 'patch choice decision' 50% of the time (192 unique model structures, at 3 starting biomass values). Vessels used 12.5% random behaviour in month 1, 25% in month 2, 37.5%, 50%, 62.5%, 75%, and 87.5% in month 3, 4, 5, 6, and 7, respectively. This averaged as 50% random behaviour over the season, with more informed behaviour at the start of the season and more random behaviour at the end of the season.

Stage 3: A comparison of the 2 previous sets of models (all informed, and 50:50 informed:random) (360 unique model structures, at 3 starting biomass values; 100% random behaviour was present in step 1 and step 2, therefore the second set were removed from the comparison to retain equal numbers of each unique model)

Box 6.2. The three stages of model selection.

A Kendall tau rank correlation coefficient (Kendall, 1938) was used to assess the correlation between the average model values and the real fishery values for the total catch, time spent steaming, time spent fishing, extent, average CPUE, average daily catch, average fuel used, and number of trips. Kendall's tau was also used to assess the correlation between monthly values of these variables in the model and the real fishery data.

The model was developed in Netlogo modelling software version 5.1.0 (Wilensky, 1999). Model simulations were controlled through R (R Development Core Team, 2016), using the *RNetLogo* package (Thiele, 2014), and run on a high performance supercomputer HPCWales (http://www.hpcwales.co.uk). The packages *tidyr* (Wickham, 2016) and *dplyr* (Wickham and Francois, 2016) were used for data processing. The ABC model selection used R code developed by van der Vaart *et al.,* (2015), which was based on the '*abc*' R package by Csillery *et al.,* (2010). The

packages *ggplot2* (Wickham, 2009), *gridExtra* (Auguie, 2016), and *splitstackshape* (Mahto, 2014) were used to visualise the outputs.

6.4. Results

6.4.1. Stage 1: How did the initial model runs perform?

In Stage 1, each combination of behavioural submodels were run, totalling 192 unique model structures, run at 3 starting biomasses, resulting in 2880 simulations. The mean values from the top 1% of models accepted in the ABC analysis were strongly correlated with the real values (Figure 6.3; Kendall tau: $r^2 = 0.93$, n=8, p<0.001). Nevertheless, these models slightly underestimated the fishing extent, and overestimated the fuel used. In these accepted models, the most common initial patch choice rule was to choose a patch at random (from patches that met the common criteria such as within maximum travel distance) (93% of accepted runs). The most common 'between patch decision' rule was to select a patch with an above average catch rate (55% of accepted runs). The most common return to port decision rule was to return at curfew (55% of accepted runs) (Table 6.3).
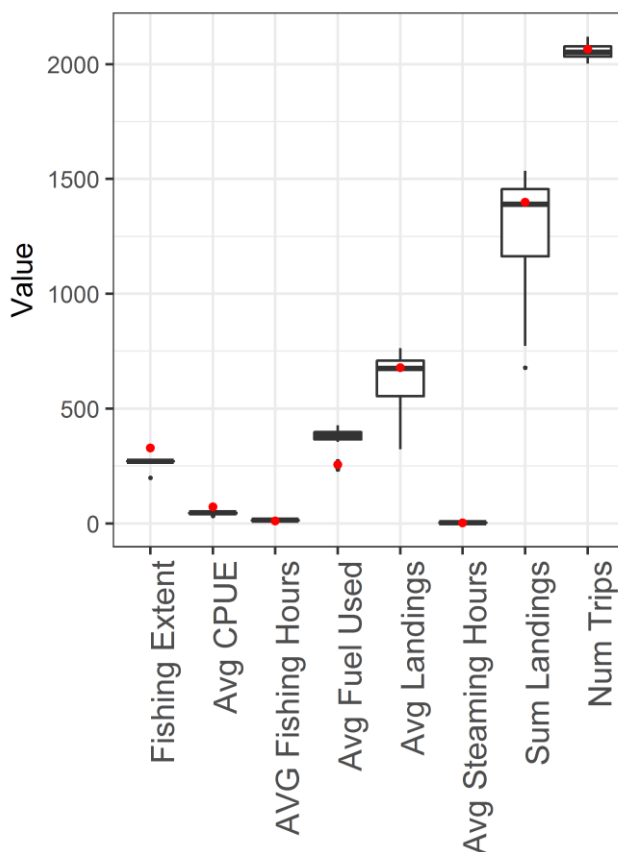
Figure 6.3. Boxplots show the output values from the accepted model runs. Red points indicate the real value from fishery data.

Table 6.3. Model settings from the accepted runs from initial uncalibrated simulations

Initial Patch Choice	Between patch Choice	Return Decision	Accepted runs
Random	Highest	At curfew	3
Random	Highest	Max fishing time	1
Random	Above average	At curfew	9
Random	Above average	Max fishing time	6
Random	Above average	After good takings	1
Random	Catch:cost ratio	At curfew	4
Random	Catch:cost ratio	Max fishing time	1
Random	Catch:cost ratio	Min viable gross	1
Random	Catch:cost ratio	After good takings	1
Conjoint GUT	Catch:cost ratio	After good takings	2

The average values from the accepted model runs recreated the magnitude and trend of cumulative landings over the season well (Figure 6.4). The trend in average daily scallop catch and average daily CPUE was captured fairly well, but the magnitude was a little low for the CPUE. Vessels appeared to steam and fish for slightly too long in the model, consequently using too much fuel.

The trend in extent was not very well recreated by the model. In the real system, the extent of fishing was relatively concentrated in the first month of the season, increasing as the season progressed, but in the model, the extent was not concentrated enough at the start of the season, nor dispersed enough at the end of the season. The model did show a slight increase in extent as the season progressed, but the magnitude of this increase was substantially lower than reality.

The best performing model structures therefore performed reasonably well, but the spatial patterns in effort could be better reproduced, and in addition, vessels spent too long at sea and consequently used too much fuel. Nevertheless, the accepted runs were only the models that performed best overall. It may be that other model structures recreated some of the spatial patterns better, and may indicate behaviours that need to be better accounted for in the model.
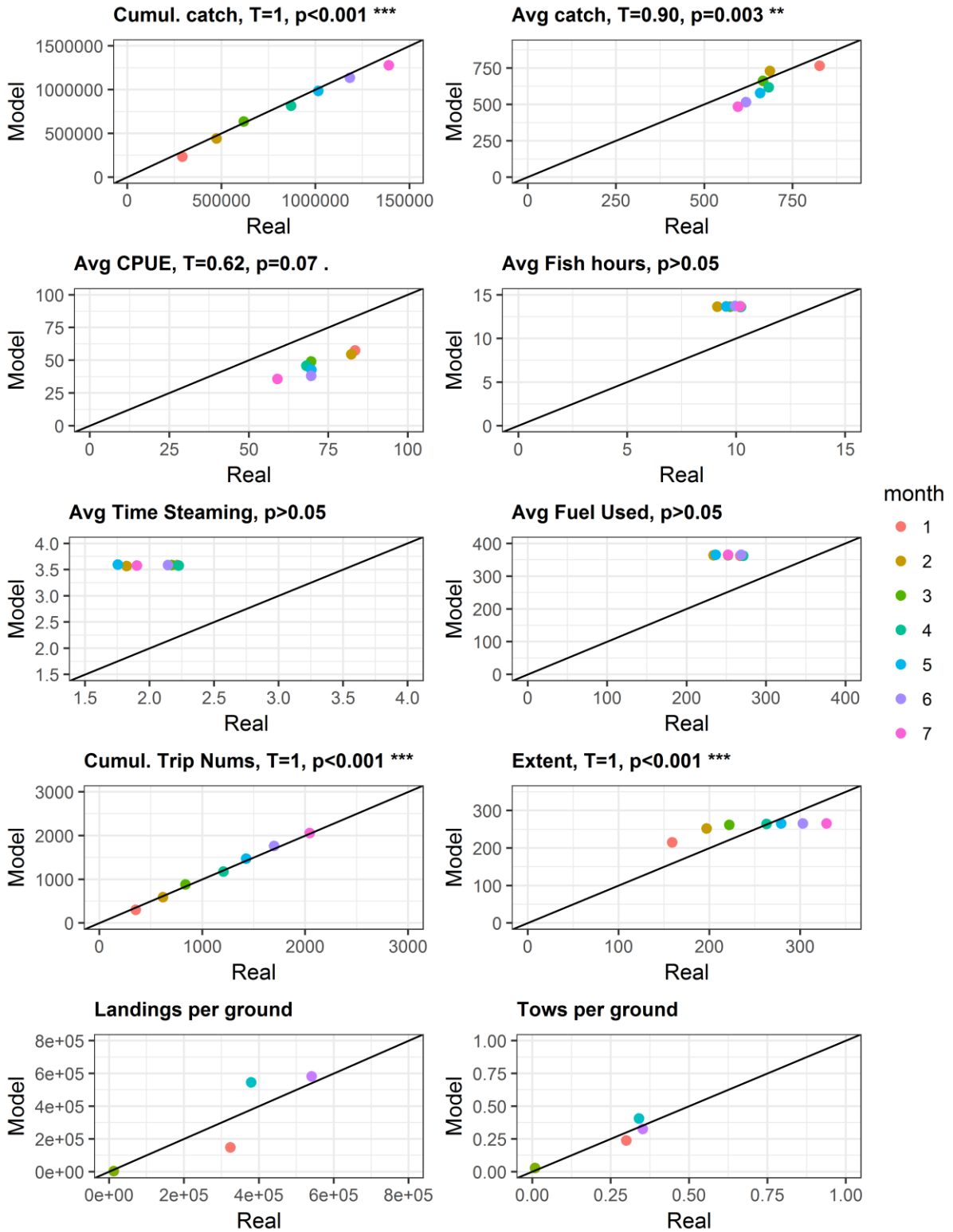
Figure 6.4. Comparison of the average values from the accepted models against the real fishery values, across the season.

6.4.2. Stage 1: How did all model structures perform?

When looking at all model runs (i.e. not just the best performing 1% of runs, but all possible combinations of behavioural rules / submodels) we can see that sometimes different submodels were better able to recreate each of the main values in the real data (Figure 6.5). The boxplots were coloured according to the initial 'patch choice decision' (Figure 6.5a), the 'between patch decision' (Figure 6.5b), the 'return to port' decision (Figure 6.5c) and the 'starting biomass' (Figure 6.5d) to see which submodels influenced how well each variable was recreated.

The average hours spent fishing and the fuel used were similar between all initial 'patch choice decision' rules, which suggests that this behavioural rule has little impact on these variables (Figure 6.5a). The initial 'patch choice decision' did influence the accuracy of the total scallops caught, the average catch, the average CPUE, the time spent steaming, and the extent of fishing, with some rules giving more accurate values than others. In particular, for the time spent steaming, rules based on a catch cost ratio and the conjoint analysis were able to accurately recreate the time spent steaming (which could be considered a proxy for distance travelled from port), whereas all other patch choice rules overestimated this. The initial 'patch choice decision' can also impact the number of trips taken, but only when using a GUT to decide where to fish, as it is the only behavioural setting for which a vessel will not fish if they cannot find a patch that satisfies that certain criteria (i.e. possible patch above a threshold giving up rate); in all other models vessels fish according to a probability based on previous patterns in effort. All models underestimated the total extent of fishing, but a random patch choice decision gave the most accurate representation of the total fishing extent.

The 'between patch decision' did not appear to be a strong driving influence on any of the variables (Figure 6.5b). However, similar to the initial patch choice, when using a GUT to decide where to fish, vessels moved patches if a neighbouring patch satisfied the criteria of a catch rate above the giving up threshold, and if none did, it returned to port.

The return to port decision rules strongly influenced the time spent fishing and the fuel used, and also influenced the amount of scallops caught and the catch rates (Figure 6.5c). Models in which vessels returned to port after achieving their minimum viable catch, or what they considered 'good takings', performed better in terms of the time spent fishing and the fuel used than models in which vessels remained fishing until they hit curfew, or the maximum time they would be willing/able to fish for.

The starting biomass did not influence the time spent fishing, time spent steaming, fuel use, number of trips, or extent, but an increased starting biomass did intuitively lead to an increase in the catch rates and total scallops caught (Figure 6.5d).
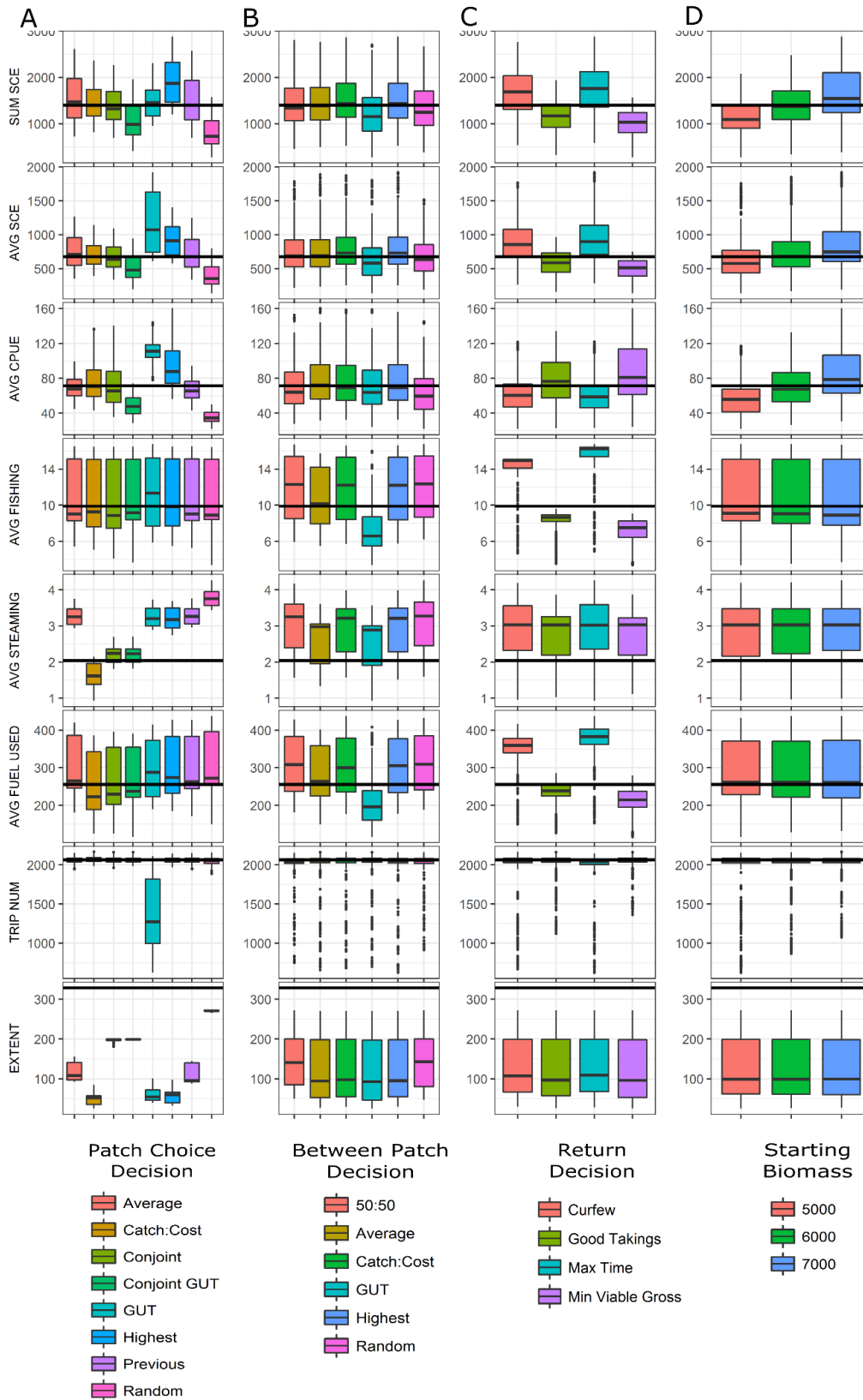
Figure 6.5. Boxplots to display all model output values. The black line indicates the real fishery value. The boxplots are coloured by a) the initial 'patch choice decision', b) the 'between patch decision', c) the 'return to port' decision, and d) the starting biomass. The sum of scallops landed is displayed in 000s.

6.4.3. Stage 1: How did all model structures perform each month?

As the fishing season progressed, the average CPUE decreased slightly in the real fishery data. The CPUE decreased across the season in all models, but the magnitude of catches were too high for some models and too low for others (Figure 6.6a). Using a 'perfectly' informed initial 'patch choice decision' such as catch cost ratio, highest conjoint score, above a GUT, or the highest expected CPUE, catch rates were over-estimated at the start of the season. All models recreated the trend of decreasing CPUE as the season progressed; however, some consistently underestimated the magnitude of CPUE (e.g. conjoint GUT, random); some overestimated the scale of the decrease, i.e. depleted the stock too quickly (e.g. highest conjoint, catch:cost ratio, highest expected catch); and some captured the trend and magnitude relatively well (e.g. above average, based on previous effort).

The time spent steaming was consistent across the season, a pattern which all models recreated, apart from the GUT patch decision model, where vessels did not fish later in the season if there was no patch with an expected catch rate above the giving up threshold (Figure 6.6b). Nevertheless, the actual time spent steaming was only accurate with models based on a catch cost ratio or the conjoint utility scores.

The extent of fishing increased as the season progressed in the real fishery data. Whilst the fishing extent also tended to increase as the season progressed in the model, the magnitude of the extent was too low. Using a random patch choice achieved the most realistic final extent of fishing (Figure 6.6c), but at the start of the season it overestimated the extent. At the start of the season an initial patch choice based on an above average conjoint score best recreated the fishing extent, with models based on above average expected catch rates, and based on previous effort, performing similarly well to the random patch choice (although these underestimated the extent whereas random patch choice overestimated the extent). However, as the season progressed, it was the models based on random patch choice that best predicted the extent. A combination of informed and random behaviour may better recreate spatial patterns of fishing in a model.
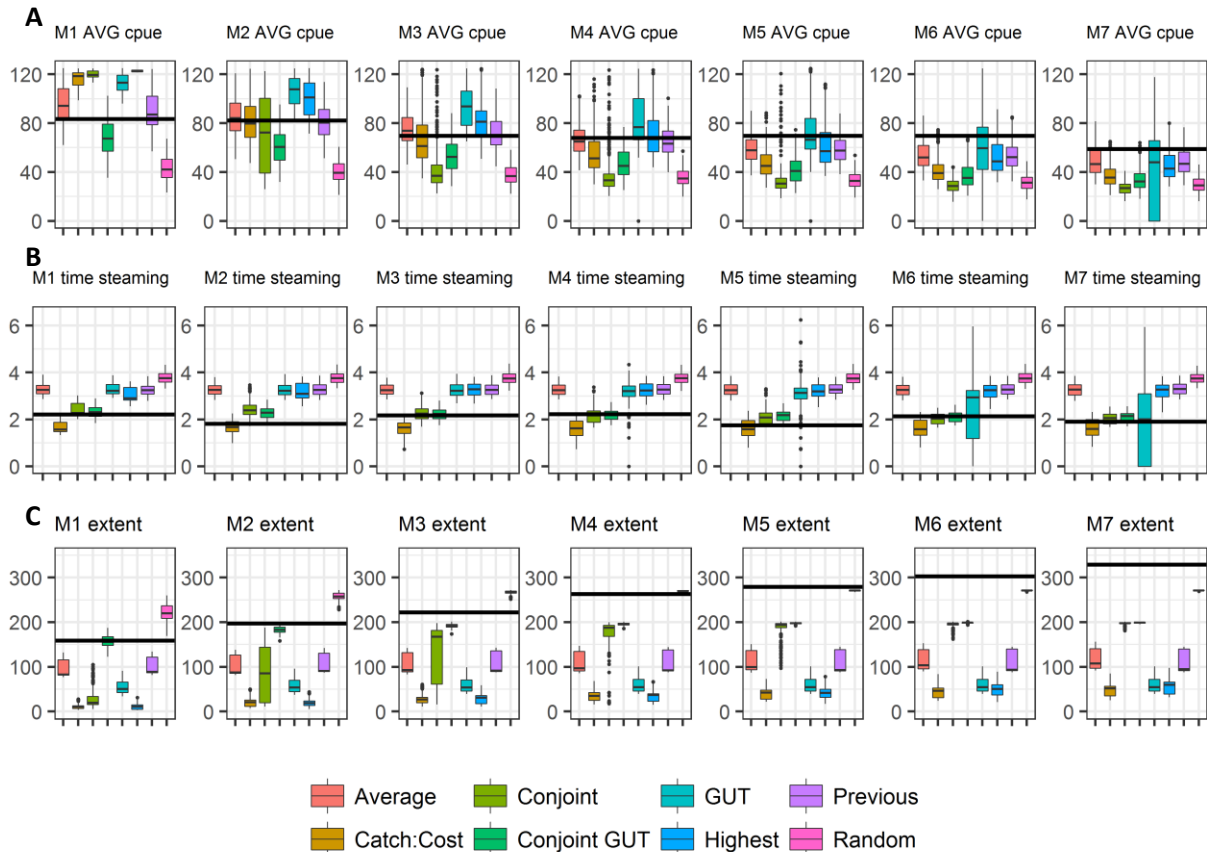
Figure 6.6. Output values from all initial patch choice submodels, for each month in the fishing season. M1 refers to month 1, M2 refers to month 2, etc.

The number of hours spent fishing were consistently most accurate across the season when deciding to return to port either after a minimum viable gross or a value considered 'good takings' had been achieved (Figure 6.7a). The amount of fuel used was also best described by deciding to return to port either after a minimum viable gross, or a value considered 'good takings', had been achieved (Figure 6.7b). The initial 'patch choice decision' had the greatest impact on the steaming time (Figure 6.6b), but the return to port decision had the biggest influence on fishing hours (Figure 6.7a); as they spent more time fishing than steaming, the return to port decision had the biggest influence on the fuel usage. The higher spread in the hours spent fishing and fuel used towards the end of the season, and particularly when returning to port at curfew or after a maximum possible fishing time, was due to some instances of zero fishing hours, when fishers were following the 'patch choice decision' of only fishing if a patch satisfied the criteria of being above a giving up threshold catch rate.

A

B
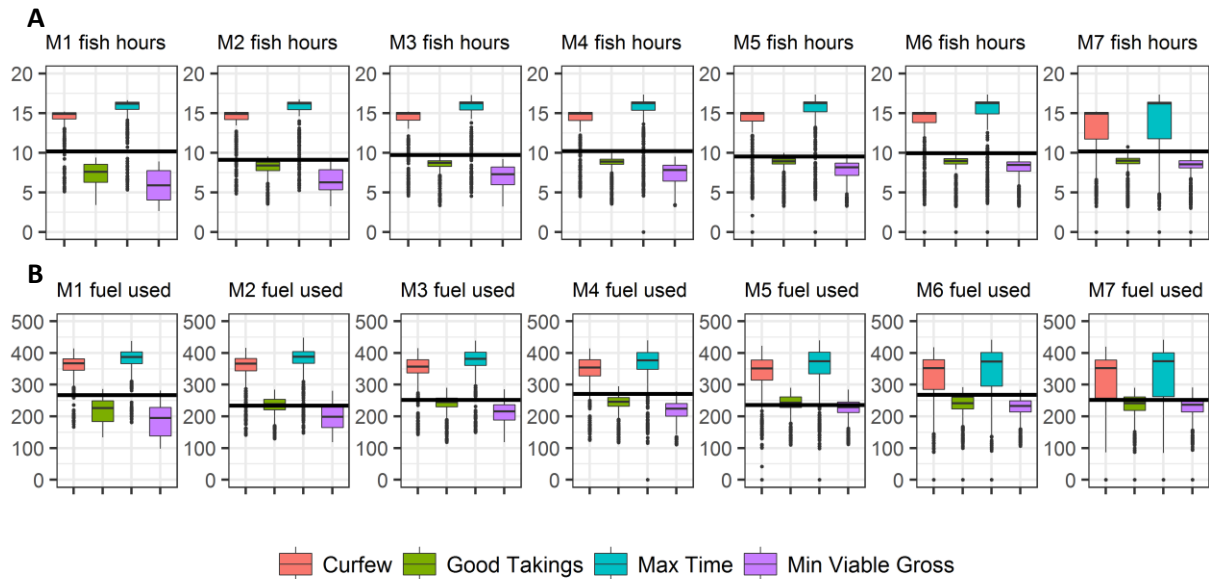
Figure 6.7. Output values from all return to port submodels, for each month in the fishing season. M1 refers to month 1, M2 refers to month 2, etc.

6.4.4. Stage 2: How does the model perform if fishers make 'informed' decisions for half the time, and act at random half of the time?

The output values from the accepted, best performing model runs using 50:50 informed:random behaviour were closely matched to the real fishery data (Kendall tau = 0.93, n=8, p<0.001) (Figure 6.8). These model runs better recreated the fuel use compared to only using informed behaviour. Nevertheless the average daily landings and the total landings over the season were lower in the 50:50 random:informed patch choice models.

In these accepted models, the most common initial patch choice rule (in combination with 50% random) was to base the decision on an above average conjoint utility score (55% of accepted runs). The most common 'between patch decision' rule was to select a patch with above average expected catch rates (45% of accepted runs). The four return to port decision rules were all present in roughly equal proportions (20-30% each) (Table 6.4).
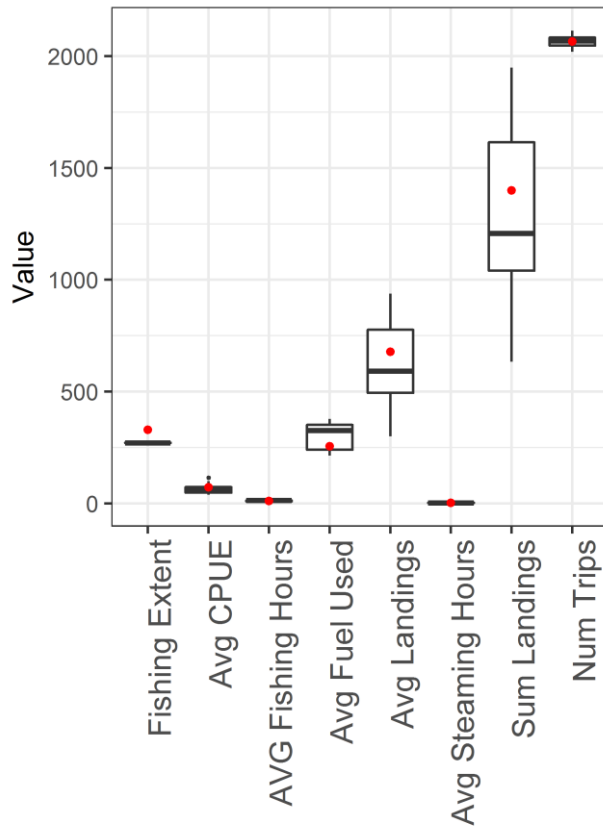
Figure 6.8. Boxplots show the output values from the accepted model runs. Red points indicate the real value from fishery data.

Table 6.4. Accepted runs from 50% informed 50% random initial patch choice

Initial Patch Choice	Between patch Choice	Return Decision	Accepted runs
Catch cost ratio	Random	Min viable gross	2
Catch cost ratio	Random	After good takings	1
Catch cost ratio	50:50 random:highest	At curfew	1
Catch cost ratio	50:50 random:highest	Min viable gross	1
Catch cost ratio	50:50 random:highest	After good takings	4
Catch cost ratio	Above average	At curfew	1
Catch cost ratio	Above average	Max fishing time	2
Highest conjoint	50:50 random:highest	Min viable gross	1
Above average conjoint	Random	Min viable gross	1
Above average conjoint	Highest	At curfew	1
Above average conjoint	50:50 random:highest	Min viable gross	1
Above average conjoint	50:50 random:highest	After good takings	2
Above average conjoint	Above average	At curfew	6
Above average conjoint	Above average	Max fishing time	4
Above average conjoint	Catch cost ratio	Min viable gross	1

Compared to the models which did not use 50% random behaviour, the trend in fishing extent over the season was improved (Figure 6.9). Nevertheless, the model still reached a maximum extent lower than the real system. The proportion of trips made to each ground were also improved, as were the trends in time spent steaming, fishing, and fuel used (Figure 6.9).
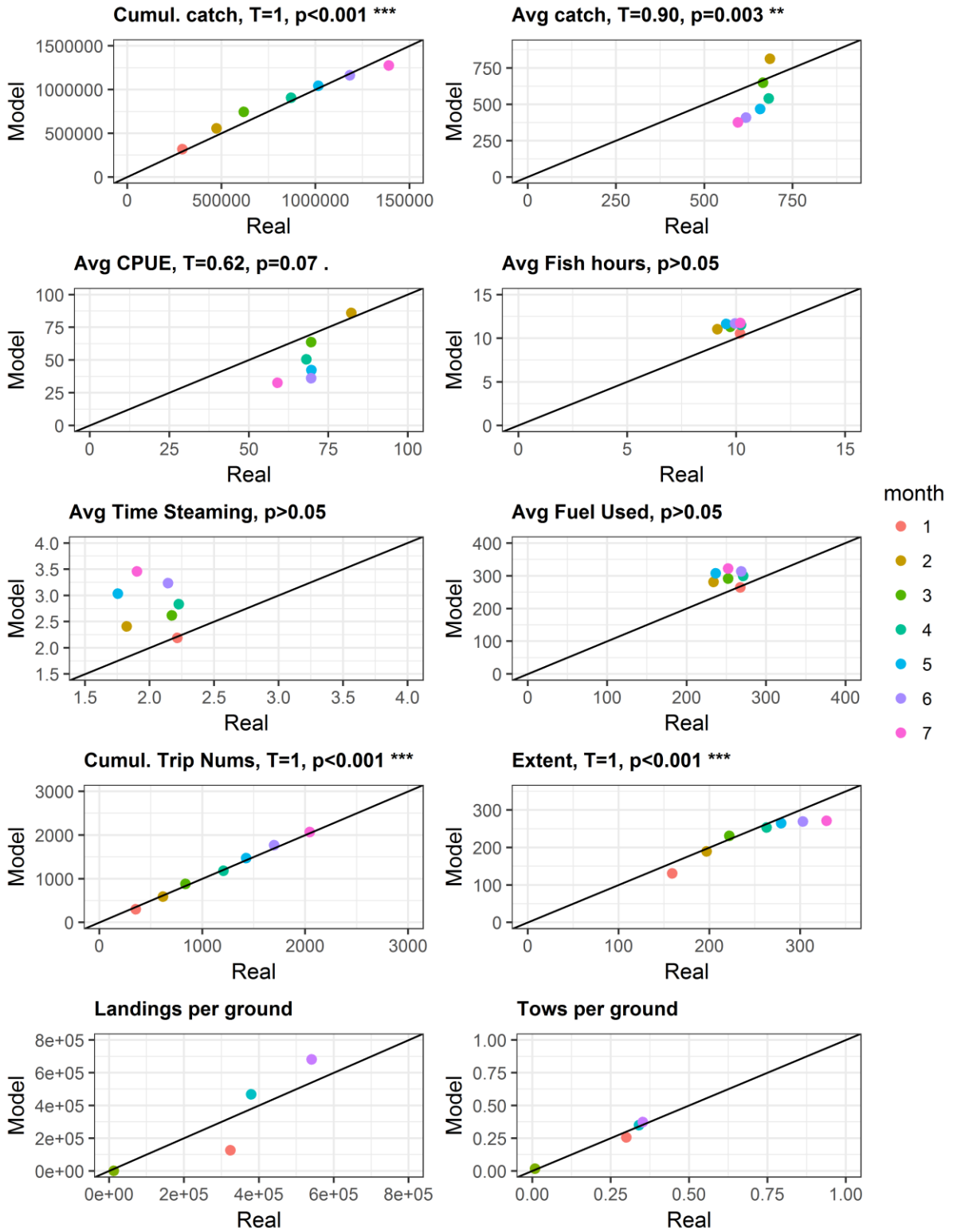
Figure 6.9. Comparison of the average values from the accepted models against the real fishery values, across the season.

The trend in fishing extent throughout the season was substantially improved by requiring vessels to use 50% informed behaviour and 50% random behaviour (Figure 6.10c). However, through introducing more random, less informed behaviour, the catch rates reduced (Figure 6.10a), and the time spent steaming increased (Figure 6.10b), making both values slightly less accurate. Therefore, whilst the extent estimate was improved by increasing the proportion of random behaviour, this led to a worsening of the predicted time steaming (a proxy for distance travelled from port).
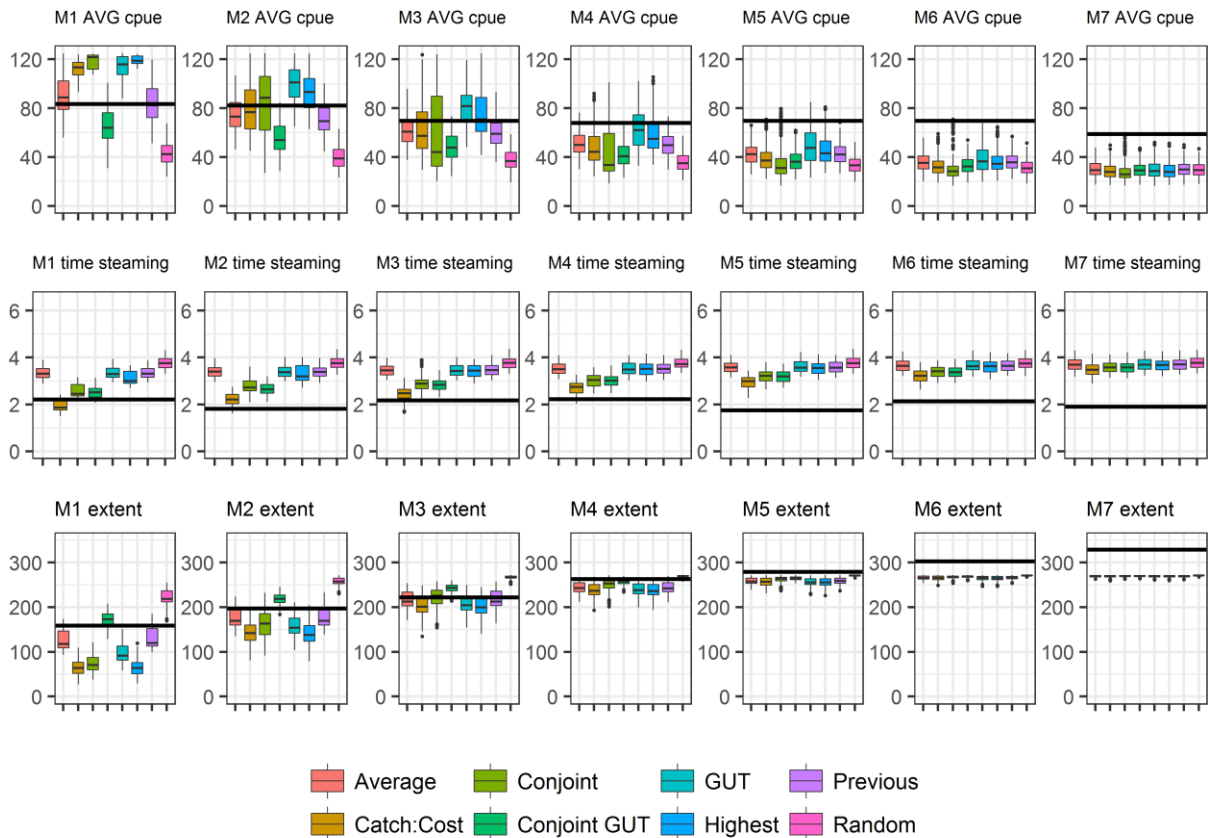
Figure 6.10. Output values from all return to port submodels, for each month in the fishing season. M1 refers to month 1, M2 refers to month 2, etc.

6.4.5. Stage 3: Did the 50:50 random:informed models perform better than the 100% informed models?

Using ABC model selection on all models (i.e. all models run so far, that use 100% informed behaviour, and 50:50 informed:random patch choice), the overall best performing models (accepted runs) were those that had 50% random behaviour (65% of accepted models used 50% random

behaviour) and 24% of accepted models used a completely random patch choice. In other words, only 11% of all accepted models had 0% random patch choice behaviour (Table 6.5).

In the accepted models, the most common initial patch choice rule was to base the decision on an above average conjoint score (56% of accepted runs). The most common 'between patch decision' rule was to select a patch with above average expected catch rates (56% of accepted runs). The most common return to port decision rule was to return to port at curfew (44%) with returning after good takings was achieved as the second most common (28%) (Table 6.5). The summary model outputs were close to the real fishery values (Figure 6.11). The trends over the season were also predicted reasonably well, although the steaming time remained slightly high (Figure 6.12).
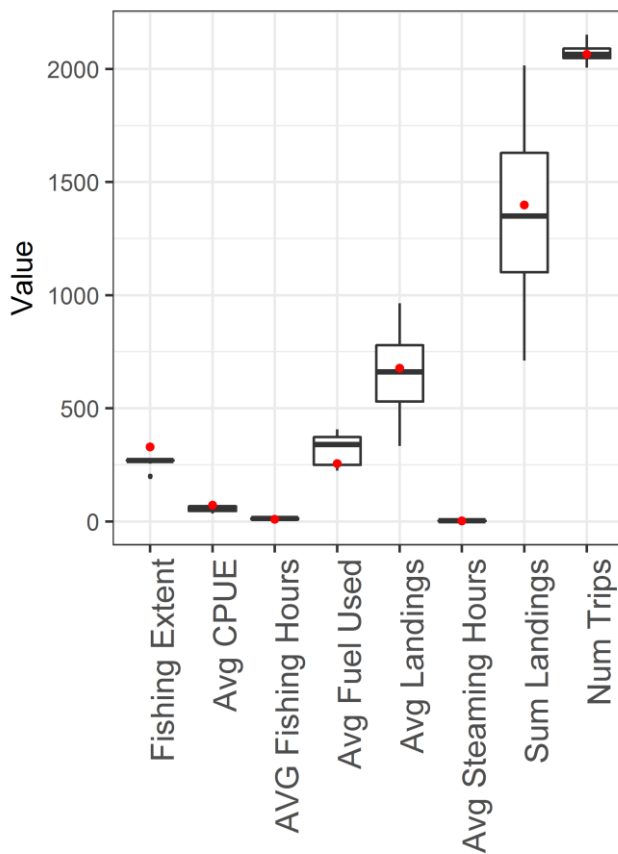
Figure 6.11. Boxplots show the output values from the accepted model runs. Red points indicate the real value from fishery data.

Table 6.5. Accepted runs from all models (100% informed and 50:50 informed:random)

Initial Patch Choice	Between patch Choice	Return Decision	% random	Accepted runs
Random	Highest	At curfew	0	1
Random	Above average	At curfew	0	8
Random	Above average	Max fishing time	0	4
Above average	Highest	After good takings	0.5	1
Above average	Above average	After good takings	0.5	1
Catch cost ratio	Highest	After good takings	0.5	1
Catch cost ratio	Above average	At curfew	0.5	3
Catch cost ratio	Above average	Max fishing time	0.5	2
Previous effort	Highest	After good takings	0.5	1
Previous effort	Above average	At curfew	0.5	1
Previous effort	Catch cost ratio	Min viable gross	0.5	1
Above average conjoint	Highest	At curfew	0.5	2
Above average conjoint	Highest	After good takings	0	2
Above average conjoint	Highest	After good takings	0.5	3
Above average conjoint	50:50 random:highest	After good takings	0	1
Above average conjoint	Above average	At curfew	0.5	6
Above average conjoint	Above average	Max fishing time	0.5	4
Above average conjoint	Above average	Min viable gross	0.5	1
Above average conjoint	Catch cost ratio	At curfew	0.5	3
Above average conjoint	Catch cost ratio	Max fishing time	0.5	1
Above average conjoint	Catch cost ratio	Min viable gross	0.5	2
Above average conjoint	Catch cost ratio	After good takings	0	3
Above average conjoint	Catch cost ratio	After good takings	0.5	2

Figure 6.12. Comparison of the average values from the accepted models against the real fishery values, across the season.

6.5. Discussion

An IBM was developed for the Isle of Man scallop fishery, which recreated fishing activity with reasonable accuracy. The development process increased our understanding of fishing behaviour in the Isle of Man scallop fishery, and provided lessons and insights for how to predict fishing behaviour in a model setting. In particular, it highlighted the importance of including a random component of fishing behaviour, rather than only using fully informed behaviour. This random component does not suggest that fishers are choosing where to fish 'randomly' as such, but that there may be processes not explicitly accounted for in a model (such as habit, personal preference, or hunches), that can be somewhat accounted for with a random component in the model structure.

6.5.1. Is the model any good?

Using simple foraging decision rules, parameterised using data collected directly from fishermen, it was possible to build an IBM that could reproduce patterns seen in the Isle of Man scallop fishery with reasonable accuracy. The model was able to reproduce realistic values for the fishing extent, average trip CPUE, average fishing hours per trip, average steaming hours per trip, average fuel used, average landings, and total landings across the fishing season without any calibration of the parameters provided by fishermen. The questionnaire data used to parameterise the model was demonstrated to be accurate and reliable when compared with similar parameters derived directly from VMS and logbook data (Chapter 2), and the lack of calibration of these parameters required to recreate patterns seen in the fishery provides further evidence to support the utility of data collected directly from fishermen (O'Donnell *et al.*, 2012; Shepperson *et al.*, 2014, 2016; Teixeira *et al.*, 2013).

There is not necessarily one model that best describes a system; there may be multiple model structures capable of recreating the same patterns in a system, using different processes and mechanisms (Csillery *et al.*, 2010). In this analysis multiple model structures were retained in the final stage of model selection, which could be run together as a suite of models that together simulate the likely range of possible impacts of management. Nevertheless, if the management objective is more focussed, it may be possible to optimise the model selection to focus on more reliably predicting one aspect of the fishery. Different model structures were better able to reproduce different patterns in the fishery. For example, the trend in fishing extent could be best captured when using 50% informed behaviour and 50% random behaviour. Different patterns in the fishery were more or less sensitive to different submodels, for example, the return to port decision

strongly influenced the time spent fishing and consequently the fuel usage, and the initial patch choice decision had a strong influence on the extent of fishing activity. The model was less sensitive to the different behavioural processes for deciding when and how to change fishing location.

Determining the most appropriate model structure to predict the outcome of management may also depend on the management objectives. For example, from a conservation perspective it may be more important to reliably predict changes in the extent of fishing, whereas from a fishery perspective it may be more important to reliably predict changes to catches and costs. Different stakeholders can have different definitions of 'sustainable' and may measure the success of management against different metrics (Hilborn *et al.*, 2015; Jennings *et al.*, 2014). When deciding which patterns to use to validate a model, consideration should therefore be given to the end goal of the model to ensure a comprehensive objective evaluation, and a model that is fit for purpose.

6.5.2. Lessons for Modelling Fisher Behaviour

The best performing model structures (i.e. accepted during the ABC model selection) were most commonly based on a selecting an initial patch with an above average conjoint utility score. In this submodel, vessels weighed up the expected catch rate and the distance from port in a non-linear manner (Chapter 2). The risk associated with travelling further than normal (i.e. higher cost) may be more heavily weighted than the potential gain from higher catches (Holland, 2008). In Prospect Theory, a theory of decision making under conditions of risk and uncertainty, risk preferences are influenced by nonlinear probability weighting and loss aversion (Kahneman and Tversky, 1979). In Prospect theory, firstly the decision is 'framed', by identifying a reference point (e.g. a 'normal' catch rate at a 'normal' distance from port), then outcomes are evaluated as deviations from this point, which may explain why the non-linear evaluation of catch:cost ratio in the conjoint utility model outperformed the linear evaluation of the catch:cost ratio.

When vessels fished for the entire duration of the curfew, or for the maximum time they would be willing to fish for, the time spent fishing, and consequently the fuel use, was too high compared to the real fishery data. When vessels returned to port after they had achieved a minimum viable gross, or a catch they considered 'good', the fishing duration was more realistic. This suggests that vessels could be exhibiting satisficing behaviour (Salas and Gaertner, 2004; Simon, 1955), aiming for a certain level of catch, rather than always aiming for the maximum possible catch. Thaler (1985) suggested that people consider the economic effects of decisions over a short timescale, rather than taking a more long term view of how decisions could impact their overall wealth; for example, taxi drivers have been shown to work for longer hours on days when they are receiving a low hourly rate,

and work shorter hours on days when they are achieving a higher hourly rate (Camerer *et al.*, 1997). In the best performing models, when fishers used a random patch choice, and consequently achieved lower average catch rates, they remained at sea until curfew or the maximum possible fishing time, but when they were using a more informed patch choice, they more often returned to port after achieving a threshold catch.

The importance of incorporating randomness into patch choice behaviour has been demonstrated; only 11% of the best performing models did not have any random patch choice behaviour in them. This does not imply that fishers choose where to fish at random, rather, that in a model context, it is important to include randomness. This randomness could be a proxy for more social influences on the decision of where to fish, such as gut feeling or intuition, heuristics, crew shortages, commitments on land, weather, risk aversion, inertia, or simply mis-judging where the best catch rates are (van Putten *et al.*, 2012). The accepted models with a fully random initial patch choice did, however, use an informed between patch choice; demonstrating that both random and informed model components are required.

Fishers are often assumed to be perfectly informed rational economic agents, but in reality, even if fishers could weigh up all possible combinations of behaviours to choose the course that would lead to the most profit (i.e. perfectly rational), there is evidence showing that not all fishers are driven solely by profits (Holland, 2008). In particular, inertia to change appears to have a significant impact on fishing patch choices, with tradition, familiarity, risk aversion, or pure inertia leading fishers to favour their known patches (Holland, 2008). The patch choice model based purely on previous effort constituted 6% of the best performing models. Modelling scallop fishers in the Isle of Man as perfectly informed and rational optimal foragers may likely overestimate catch rates, and underestimate the extent of fishing. In other words, fishers are not able (or choose not) to perfectly target their fishing activity to patches with the highest catch rates at all times, and to model them in this way could overestimate the capacity of economic incentives to alter behaviour (Holland, 2008; Smith and Wilen, 2005). Predicting responses to management by modelling fishers as optimal foragers may overestimate the capacity of the fleet to compensate for restrictions such as closed areas, and may underestimate the economic impact that a management measure may have on the fishery. It may also underestimate the extent of fishing, underestimating the environmental footprint of the fishery.

In an IBM it is also possible for individuals to 'learn' behaviour (Grimm and Railsback, 2005), such as learning what behaviours provide the best catch rates, and remembering where the best profits were achieved. Including learning behaviours in a model may allow it to predict over longer

timescales, as fishers would be able to better respond and adapt to changing conditions over time. However, caution would be required to prevent model vessels fishing unrealistically successfully.

6.5.3. Limitations of the Model

In POM, the patterns chosen for model validation should be relevant to the question being asked with the model (Railsback and Johnson, 2011). For the initial model validation, individual heterogeneity, such as variation in catches was not explicitly tested as part of the validation, although individuals in the model would have achieved different catch rates, contributing to the overall rates. More fine scale validation could provide further insights into fishing behaviour, and how management may affect fishers differently. The current model also allowed only one type of behavioural submodel to be followed by all vessels in the simulation. It could be that parameterising vessels in the model in a similar ratio as the accepted behavioural rules may provide a model that better captures the variation and individual heterogeneity within the fishery. The next stage of model development and validation could consider heterogeneity between fishing vessels, to try to predict how management may affect different individuals within the fishery.

In the model, fishers 'decide' where to fish based on a probability value, based on previous patterns in effort in the fishery. The model can therefore only be applied on a short time-scale, under the assumption that overall effort levels will remain constant. In other words, the model can only be used to predict the way that effort is distributed throughout a season, rather than predicting the overall amount of effort. The sea state, days since the start of the season, previous catches, and predicted wave conditions were shown to influence the likelihood of fishing or not on a particular day (Chapter 3), and the response also varied between individuals. It would be possible to model the decision whether to fish or not on each day; however, it is not possible to realistically predict the wave conditions over a whole season which is an important determinant (Chapter 3). Wave conditions could be simulated based on previous patterns, with models run using 'likely' probabilities of sea states. Further model development could also then include a 'climate change' mode, with increased likelihoods of prohibitive sea states. The return to port decision is also a simple binary decision currently (i.e. is it curfew? Have I caught X amount?), which could also be modelled as a decision based on multiple variables such as the duration at sea, catch, time of day, target catch, etc.

Nevertheless, including more complex submodels for the likelihood of fishing and likelihood of returning to port would make the model considerably more complex. One model simulation

currently takes an average of about 3 minutes to run on a high performance supercomputer (HPCWales); the more simple models such as random patch choice run faster than more complex models such as the conjoint analysis models in which multiple variables must be weighed up to make a decision. Increasing the complexity of the model would increase the time and resource constraints on the model. There may be a trade-off between increasing the realism of predicting the way fishers decide when to fish, with increasing model complexity, leading to more difficulty interpreting the model, and increased computer power requirements (Evans *et al.*, 2013; van der Vaart *et al.*, 2015).

6.5.4. The Model as a Tool for Fisher Participation

This model was developed using data collected directly from fishermen, without any further calibration of parameters. Using values provided by fishers should ensure realistic behaviours in the system, and the lack of calibration could help engender trust in the outputs. The next stages of model development could include stakeholder workshops in which fishers and managers are invited to offer their evaluation of the model, and suggest scenarios to be tested. The success of management can be influenced by the level of participation by fishers; better management decisions can be made when stakeholders are engaged and involved, provided the model can be effectively communicated to stakeholders and end users (Cartwright *et al.*, 2016; Mackinson *et al.*, 2011; Voinov and Bousquet, 2010). There are different levels of participation, from a more basic contribution of data, to direct participation and input to the actual model development, and participation in running model simulations (Mackinson *et al.*, 2011; Röckmann *et al.*, 2012). The use of NetLogo, an open source, user friendly modelling software, facilitates fisher participation through providing an intuitive user interface with model visualisations, and simple sliders and drop-down selectors to modify model settings and parameters (Figure 6.13).
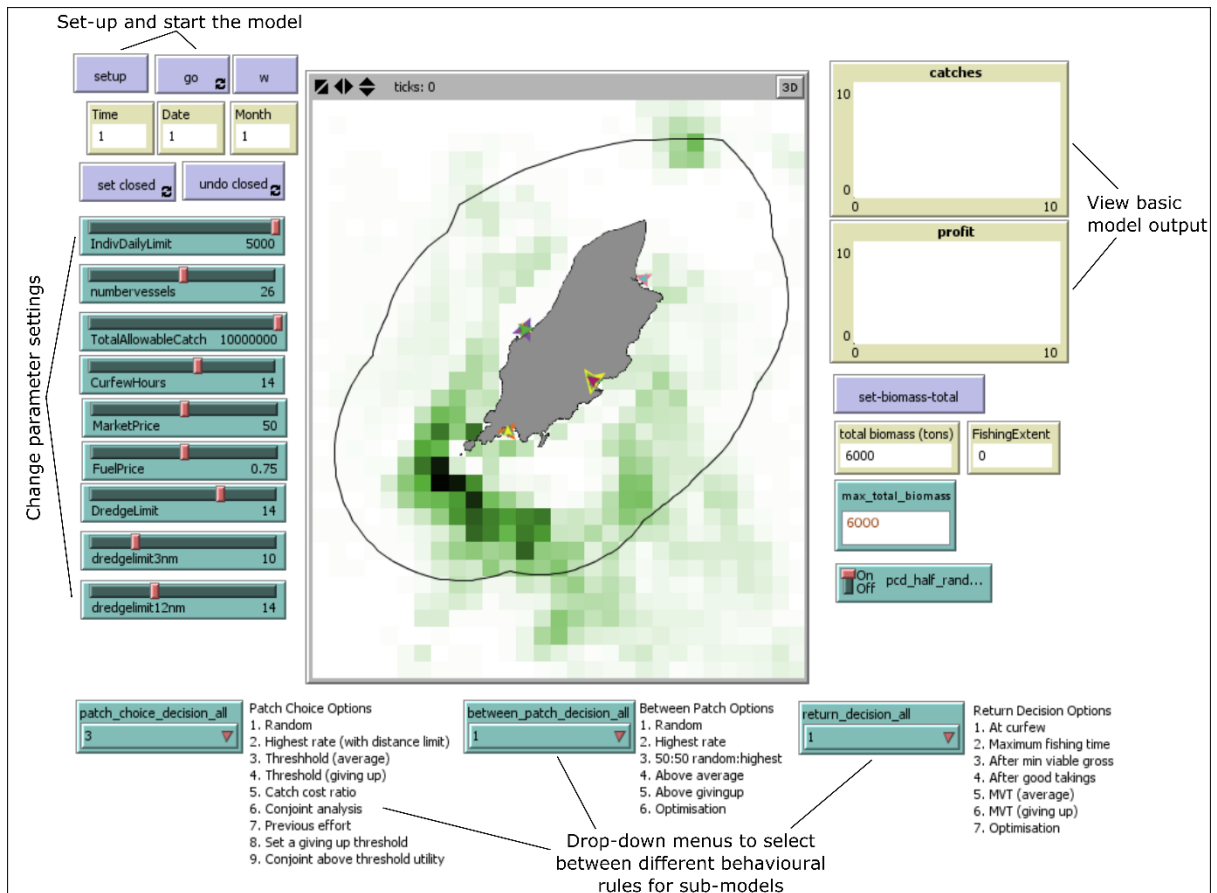
Figure 6.13. The user interface of the model in NetLogo. Sliders can be used to change parameters, and drop down-menus used to change the behavioural settings in submodels. The model runs are visualised in the centre of the interface, and simple model outputs can be observed to the top right.

6.5.5. Extending the Model to Other Fisheries

This analysis has demonstrated the importance of contrasting different submodels of behavioural

decisions in an IBM. The most realistic behaviours may differ between fisheries, however, depending

on how much the fishers deviate from an optimal foraging model, and the level of profit maximising

behaviour, risk aversion, and inertia (Holland, 2008). The model could be relatively easily

parameterised for another fishery, and the same validation process followed to determine the most

appropriate behavioural submodels for that fishery. Nevertheless, this model was developed in a

small inshore fishery, without the possibility of fishers exiting the fishery, and can thus only be

applied to questions surrounding how current levels of effort will be distributed, rather than

predicting displacement between fisheries (eg. larger more industrial fleets might have a higher

capacity to exit a fishery). Documenting the model development and validation in this way (i.e. open,

using a standardised ODD format (Grimm et al., 2006), explaining each step of model validation

(Grimm *et al.*, 2014)), facilitates transferability as the model can be applied appropriately with a full

understanding of the assumptions, decisions, and careful testing that has gone into model development.

6.6. Conclusions

Using data collected directly from fishermen, it was possible to develop a realistic IBM of the Isle of Man scallop fishery. The development process provided valuable insights into fishing behaviour in the Isle of Man scallop fishery. The ABC model validation process was informative, and demonstrated the importance of contrasting different submodels of behaviour, and exploring all model outputs. In particular, it has highlighted the importance of incorporating random, or less-informed behaviour into a model of fishing activity, and also allowing vessels to fish sub-optimally, for example not necessarily fishing for the whole time permitted. Modelling fishers as truly rational profit maximisers who conform to optimal foraging theory may overestimate fishers' capacity to compensate for management restrictions, underestimating the impact of management on them. This process could be an important step in developing an IBM of any fishery, to ensure that realistic behaviours are input to the model. A realistic model of fishing activity could then allow more realistic predictions of the responses to management.

6.7. Acknowledgements

6.8. References

Auguie, B. 2016. gridExtra: Miscellaneous Functions for 'Grid' Graphics. R package version 2.2.1. https://cran.r-project.org/package=gridExtra.

Augusiak, J., Van den Brink, P. J. and Grimm, V. 2014. Merging validation and evaluation of ecological models to 'evaludation': A review of terminology and a practical approach. Ecological Modelling, 280: 117 – 128.

Bacalso, R. T. M., Juario, J. V., and Armada, N. B. 2013. Fishers' choice of alternative management scenarios: A case study in the Danajon Bank, Central Philippines. Ocean & Coastal Management, 84: 40–53.

Begossi, A. 1992. The use of optimal foraging theory in the understanding of fishing strategies: A case from Sepetiba Bay (Rio de Janeiro State, Brazil). Human Ecology, 20: 463–475.

Begossi, A., Clauzet, M., Hanazaki, N., Lopes, P. F., and Ramires, M. 2009. Fishers' decision making, optimal foraging and management. *In* III Seminario de Gestao Socioambiental para o Desenvolvimento Sustentavel da Aquicultura e da Pesca no Brasil - III SEGAP 2009, pp. 1–5.

Bloor, I. S. M., and Kaiser, M. J. 2016. The Isle of Man Aequipecten opercularis stock assessment Fisheries and Conservation Report No. 66, Bangor University. 36 pp.

Burgess, M., Drexler, M., Axtell, R., Bailey, R., Watson, J., Ananthanaryanan, A., Cabral, R., *et al.* 2017. The role of agent-based modeling in systems-based fishery management. Fish and Fisheries (In Review).

Camerer, C., Babcock, G., Loewenstein, G., and Thaler, R. 1997. Labor Supply of New York City Cabdrivers: One Day at a Time. Quarterly Journal of Economics, 112: 407–441.

Cartwright, S. J., Bowgen, K. M., Collop, C., Hyder, K., Nabe-Nielsen, J., Stafford, R., Stillman, R. A., *et al.* 2016. Communicating complex ecological models to non-scientist end users. Ecological Modelling, 338: 51–59.

Charles, A. T. 1995. Fishery Science - the Study of Fishery Systems. Aquatic Living Resources, 8: 233–239.

Charnov, E. L. 1976. Optimal Foraging, the Marginal Value Theorem. Theoretical Population Ecology, 9: 129–136.

Csillery, K., Blum, M. G. ., Gaggiotti, O. E., and Francois, O. 2010. Approximate Bayesian Computation (ABC) in practice. Trends in Ecology & Evolution, 25: 410–418.

de Oliveira, L. E. C., and Begossi, A. 2011. Last Trip Return Rate Influence Patch Choice Decisions of Small-Scale Shrimp Trawlers: Optimal Foraging in São Francisco, Coastal Brazil. Human Ecology, 39: 323–332.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES Journal of Marine Science, 60: 371–380.

Dowling, N. a, Wilcox, C., Mangel, M., and Pascoe, S. 2012. Assessing opportunity and relocation costs of marine protected areas using a behavioural model of longline fleet dynamics. Fish and Fisheries, 13: 139–157.

Evans, M. R. 2012. Modelling ecological systems in a changing world. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 181–190.

Evans, M. R., Grimm, V., Johst, K., Knuuttila, T., de Langhe, R., Lessells, C. M., Merz, M., *et al.* 2013. Do simple models lead to generality in ecology? Trends in Ecology & Evolution, 28: 578–83.

Fulton, E. a, Smith, A. D. M., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Gordon, H. S. 1953. An economic approach to the optimum utilization of fishery resources. Journal of the Fisheries Research Board of Canada, 10: 442–457.

Grimm, V., Augusiak, J., Focks, A., Frank, B. M., Gabsi, F., Johnston, A. S. A., Liu, C., *et al.* 2014. Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. Ecological Modelling, 280: 129–139.

Grimm, V., and Railsback, S. F. 2005. Individual-Based Modeling and Ecology. Princeton University Press, Princeton.

Grimm, V., and Railsback, S. F. 2012. Pattern-oriented modelling: a 'multi-scope' for predictive systems ecology. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 298–310.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H. H., *et al.* 2005. Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. Science, 310: 98-991.

Hallwass, G., Lopes, P. F. M., Juras, A., and Silvano, R. 2013. Behavioral and environmental influences on fishing rewards and the outcomes of alternative management scenarios for large tropical

rivers. Journal of Environmental Management, 128: 274–82.

Hanley, L., Read, A., McHarg, K., Eastwood, C., Hamilton, A., Milsom, N., Eaton, J., *et al.* 2013. Commercial Fisheries and Sea Angling. *In* Manx Marine Environmental Assessment. Isle of Man Plan. Isle of Man Government., p. 64. Ed. by Hanley et al.

Hilborn, R. 2007. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Hilborn, R., Fulton, E. A., Green, B. S., Hartmann, K., Tracey, S. R., and Watson, R. A. 2015. When is a fishery sustainable ? Canadian Journal of Fisheries and Aquatic Sciences, 1441: 1–46.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., *et al.* 2004. When can marine reserves improve fisheries management? Ocean & Coastal Management, 47: 197–205.

Holland, D. 2008. Are Fishermen Rational? A Fishing Expedition. Marine Resource Economics, 23: 325–344.

Jennings, S., Smith, A. D. M., Fulton, E. A., and Smith, D. C. 2014. The ecosystem approach to fisheries: management at the dynamic interface between biodiversity conservation and sustainable use. Annals of the New York Academy of Sciences, 1322: 48–60.

Kendall, M. G. 1938. A new measure of rank correlation. Biometrika, 30: 81–93.

Lambert, G. I., Jennings, S., Hiddink, J. G., Hintzen, N. T., Hinz, H., Kaiser, M. J., and Murray, L. G. 2012. Implications of using alternative methods of vessel monitoring system (VMS) data analysis to describe fishing activities and impacts. ICES Journal of Marine Science, 69: 682–693.

Lee, J., South, a. B., and Jennings, S. 2010. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES Journal of Marine Science, 67: 1260–1271.

Lee, A. Van Der, Gillis, D. M., and Comeau, P. 2014. Comparative analysis of the spatial distribution of fishing effort contrasting ecological isodars and discrete choice models. Canadian Journal of Fisheries and Aquatic Sciences, 150: 141–150.

Little, L. R., Punt, A. E., Mapstone, B. D., Begg, G. a., Goldman, B., and Williams, A. J. 2009. An agent-based model for simulating trading of multi-species fisheries quota. Ecological Modelling, 220: 3404–3412.

MacArthur, R. H., and Pianka, E. R. 1966. On Optimal Use of a Patchy Environment. The American

Naturalist, 100: 603–609.

Mackinson, S., Wilson, D. C., Galiay, P., and Deas, B. 2011. Engaging stakeholders in fisheries and marine research. Marine Policy, 35: 18–24.

Mahto, A. 2014. splitstackshape: Stack and Reshape Datasets After Splitting Concatenated Values. R package version 1.4.2. https://cran.r-project.org/package=splitstackshape.

Marchal, P., Poos, J.-J., and Quirijns, F. 2007. Linkage between fishers' foraging, market and fish stocks density: Examples from some North Sea fisheries. Fisheries Research, 83: 33–43.

Murray, L., Hinz, H., and Kaiser, M. 2011. Functional response of fishers in the Isle of Man scallop fishery. Marine Ecology Progress Series, 430: 157–169.

O'Donnell, K. P., Molloy, P. P., and Vincent, A. C. 2012. Comparing Fisher Interviews, Logbooks, and Catch Landings Estimates of Extraction Rates in a Small-Scale Fishery. Coastal Management, 40: 594–611.

Orians, G. H., and Pearson, E. 1979. On the Theory of Central Place Foraging. *In* Analysis of Ecological Systems. Ed. by D. J. Honrs, G. R. Stairs, and R. D. Mitchell. Ohio State University, Columbus.

Pascoe, S., and Mardle, S. 2005. Anticipating fisher response to management: Can economics help? ICES Annual Science Conference. Aberdeen.

Plagányi, E. E., Punt, A. E., Hillary, R., Morello, E.B., Thébaud, O., Hutton T., Pillans, R. D., Thorson, J. T., Fulton, E. A., Smith, A. D. M., Smith, F., Bayliss, P., Haywood, M., Lyne, V., Rothlisberg, P.C. 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries, 15 (1): 1 – 22.

Pritchard, J. K., Seielstad, M. T., Perez-Lezaun, A., and Feldman, M. W. 1999. Population growth of human Y chromosomes: a study of Y chromosome microsatellites. Molecular Biology and Evolution, 16: 1791–1798.

R Development Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/.

Railsback, S. F., and Johnson, M. D. 2011. Pattern-oriented modelling of bird foraging and pest control in coffee farms. Ecological Modelling, 222: 3305–3319.

Rijnsdorp, a. 2000. Competitive interactions among beam trawlers exploiting local patches of flatfish in the North Sea. ICES Journal of Marine Science, 57: 894–902.

Ripley, B. D. 2004. Selecting amongst large classes of models. *In* Methods and Models in Statistics: In Honour of Professor John Nelder, FRS, pp. 155–170. Ed. by N. Adams and E. Al. Imperial College Press.

Röckmann, C., Ulrich, C., Dreyer, M., Bell, E., Borodzicz, E., Haapasaari, P., Hauge, K. H., *et al.* 2012. The added value of participatory modelling in fisheries management – what has been learnt? Marine Policy, 36: 1072–1085.

Salas, S., and Gaertner, D. 2004. The behavioural dynamics of fishers: management implications. Fish and Fisheries, 5: 153–167.

Shepperson, J., Murray, L. G., Cook, S., Whiteley, H., and Kaiser, M. J. 2014. Methodological considerations when using local knowledge to infer spatial patterns of resource exploitation in an Irish Sea fishery. Biological Conservation, 180: 214–223.

Shepperson, J., Murray, L. G., Mackinson, S., Bell, E., and Kaiser, M. J. 2016. Use of a choice-based survey approach to characterise fishing behaviour in a scallop fishery. Environmental Modelling & Software, 86: 116–130.

Simon, H. . 1955. A Behavioural Model of Rational Choice. The Quarterly Journal of Economics, 69: 99–118.

Smith, M. D., and Wilen, J. E. 2005. Heterogeneous and Correlated Risk Preferences in Commercial Fishermen: The Perfect Storm Dilemma. Journal of Risk and Uncertainty, 31: 53–71.

Sosis, R. 2002. Patch Choice Decisions among Ifaluk Fishers. American Anthropologist, 104: 583–598.

Teixeira, J. B., Martins, A. S., Pinheiro, H. T., Secchin, N. A., Leão de Moura, R., and Bastos, A. C. 2013. Traditional Ecological Knowledge and the mapping of benthic marine habitats. Journal of Environmental Management, 115: 241–50.

Thaler, R. 1985. Mental Accounting and Consumer Choice. Marketing Science, 4: 199–214.

Thiele, J. C. 2014. R Marries NetLogo: Introduction to the RNetLogo Package. Journal of Statistical Software, 58: 1–41.

Topping, C. J., Høye, T. T., and Olesen, C. R. 2010. Opening the black box—Development, testing and documentation of a mechanistically rich agent-based model. Ecological Modelling, 221: 245–255.

van der Vaart, E., Beaumont, M. A., Johnston, A. S. A., and Sibly, R. M. 2015. Calibration and evaluation of individual-based models using Approximate Bayesian Computation. Ecological

Modelling, 312: 182–190.

van Putten, I. E., Kulmala, S., Thébaud, O., Dowling, N., Hamon, K. G., Hutton, T., and Pascoe, S. 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish and Fisheries, 13: 216–235.

Voinov, A., and Bousquet, F. 2010. Modelling with stakeholders. Environmental Modelling & Software, 25: 1268–1281.

Wickham, H. 2009. Elegant Graphics for Data Analysis. Springer-Verlag, New York.

Wickham, H. 2016. tidyr: Easily Tidy Data with `spread()` and `gather()` Functions. R package version 0.4.1. https://cran.r-project.org/package=tidyr.

Wickham, H., and Francois, R. 2016. dplyr: A Grammar of Data Manipulation. R package version 0.5.0. https://cran.r-project.org/package=dplyr.

Wilen, J. E., Smith, M. D., Lockwood, D., and Botsford, L. W. 2002. Avoiding Surprises: Incorporating Fishermen Behaviour into Management Models. Bulletin of Marine Science, 70: 553–575.

Wilensky, U. 1999. NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. http://ccl.northwestern.edu/netlogo/.

CHAPTER 7: Predicting the Behavioural Response of Fishermen to Management, using an Individual-based Model

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All work completed by JS, with supervisory input from LGM, EB, SM and MJK.

7.1. Abstract

An individual-based model (IBM) could provide the basis of a management simulation tool for predicting the likely outcome of management, reducing unexpected or unintended consequences. However, managers need to know that a model is a sufficiently good representation of a system before they can apply it in the decision-making process. Model validation typically constitutes comparing model output data with empirical data to ensure that the discrepancies are not large enough that the model should be considered too unrealistic for use.

This chapter presented a model output corroboration of fishing activity predicted by an IBM of the Isle of Man scallop fishery, comparing model output to independent fishery data, following the implementation of new area closures. It also demonstrated the potential use of the model for exploring the likely impact of management, using a series of hypothetical area closures to explore the range of impacts on fishing footprint, catches, and fuel costs.

The IBM was able to reproduce some patterns in the independent data, but not others, leading to further hypotheses for model development and validation. For example, the model structures that best reproduced the absolute values of catches were not the model structures that best reproduced the trend or change in catches. Simulating the response to hypothetical closed areas demonstrated the potential of the model for informing management decisions, and how closing different arrangements of the 12nm Sea to fishing could have quite varying impacts on the fishery. The model predicted that large areas of low density scallop biomass could be closed to fishing, possibly even having a positive impact on the fishery, through directing fishing activity to high density scallop areas.

Fishery systems may be too complex to distil to a single 'accurate' model, but having a suite of models that together give a reasonable representation of the fishery could allow the range of likely impacts to be considered. Documenting the model development and validation ensures that the model can be applied based on a thorough understanding of its performance, the justification for the final model structure, and the uncertainty in model outputs.

7.2. Introduction

Despite ultimately working towards a common goal, sustainability can mean different things to different people (Hilborn *et al.*, 2015; Jennings *et al.*, 2014). For example, whilst both conservationists and fishermen desire a sustainable stock, the objectives and drivers of fisheries management may differ between them. A conservationist may be more concerned with protecting the seabed and all its flora and fauna, whereas a fisherman may be more concerned with maintaining a stock level that supports their livelihood. Of course, these are not mutually exclusive, but they perhaps lead different stakeholders to view systems from a different perspective. Regardless of your perspective, to be sure that management will work as intended, it is important to consider the behavioural response of fishermen (Daw, 2008; Dinmore *et al.*, 2003). For example, in 2001 the 'cod box' excluded the North Sea beam trawl fleet to protect spawning aggregations of cod. However, to compensate for this exclusion, fishers moved to a previously unfished area, resulting in a long term negative impact (Dinmore *et al.*, 2003). The success of management is dependent on its ability to modify the behaviour of the fishermen sufficiently, to bring about the intended change, whether it is reduced catches or reduced footprint (Hilborn, 2007). Fisher behaviour is, however, an area of considerable uncertainty in fisheries management and the behavioural response of fishers is often not fully considered in management planning (Fulton *et al.*, 2011).

The ability to predict the impacts of management on fishermen could allow better communication and discussion between fishers and managers about the most appropriate management solutions, reaching better compromises between objectives, and reducing unintended or unexpected consequences (Hilborn *et al.*, 2004; Pascoe and Mardle, 2005). Some management measures may be more restrictive to fishermen, whereas others may allow a simple alternative fishing strategy to prevent financial loss. For example, following an area closure, fishers may be able to easily compensate for the lost area, and maintain their catches elsewhere at little extra cost. However, if the closed area is near to port, this might mean vessels have to travel much further for catches (Daw, 2008), increasing their costs and decreasing profits. Spatial arrangements of closed areas that protect the same proportion of the stock, may therefore have different impacts on fishermen. Similarly, if the aim of the management was to reduce the total stock removal, a closed area might not do this if fishers can simply catch the same amount elsewhere. Whether a management action is considered 'successful' would therefore depend on the objective.

7.2.1. Individual-based Models could help predict outcomes of management

The behavioural response of fishermen to management is not often formally accounted for in management planning, either through oversight, or a lack of data and models that enable its consideration (Fulton et al., 2011). Individual-based models (IBMs) could help to address some of the knowledge gaps in our understanding of fisher behaviour, and allow us to create simulation tools that could help both managers and fishers better predict and understand the potential consequences of different management scenarios (Evans, 2012; Grimm and Railsback, 2005). IBMs view systems as having properties that arise from the behaviours and interactions of the individuals that make up the system (Grimm and Railsback, 2005), which lends itself well to modelling fishing behaviour, as it is the behaviours of individual fishermen that drive the spatial patterns seen in the system (Burgess *et al.*, 2017; Plaganyi *et al.*, 2014; Hilborn, 2007). IBMs present an opportunity to model complex systems with more realism than previously possible (van der Vaart *et al.*, 2015). The structure of a model is, however, a compromise between realism, complexity, and efficiency (Evans, 2012; Evans *et al.*, 2013); an IBM must capture all of the processes and heterogeneity required to understand the system, but must also not be overly computationally demanding, or so complex that parameter uncertainty renders it too complex for application.

7.2.2. Comprehensive validation of fishery IBMs is needed

Managers need to know that a model is a sufficiently good representation of a system before they can apply it in the decision-making process (Augusiak *et al.*, 2014). In particular, we must ensure that an IBM is mechanistically, or structurally, realistic, and doesn't reproduce patterns seen in a fishery for the wrong reasons, or just because it has been calibrated to do so (Augusiak *et al.*, 2014). Mechanistic modelling, such as individual-based modelling, simplifies real world processes, such as deciding where to fish, so that the system can feasibly be modelled. Clearly, this simplification means that details in model processes will be omitted, leading to inherent uncertainty, but including all relevant factors is not always feasible, due to time or monetary constraints (Augusiak *et al.*, 2014). Due to this simplification, decision-makers understandably require some form of model validation, to provide confidence that they are not going to make flawed decisions. Nevertheless, communicating the model validation process can be a challenge (Augusiak *et al.*, 2014). As models are simplified representations of real systems, it can be difficult to demonstrate that models are still realistic enough for their intended purpose, particularly as there are no universal standards or single test statistics, such as an R^2 value (Rykiel, 1996). Model validation typically constitutes comparing

model output data with empirical data to ensure that the discrepancies are not large enough that the model should be considered too unrealistic for use (Augusiak *et al.*, 2014; Grimm *et al.*, 2014). There is perhaps more value in understanding where the model matches the data and where it deviates, rather than condensing such complexity down to a single value. Nevertheless, decision-makers are more familiar with an R^2 value, or similar statistic, therefore communicating a more qualitative pattern oriented validation of a complex IBM can be a challenge (Railsback and Johnson, 2011). Comprehensively documenting the model validation stages can aid decision makers in evaluating the performance, uncertainty and appropriate application of a model (Grimm *et al.*, 2014).

7.2.3. Model Output Corroboration

Validation of IBMs often has two steps; a model output verification process in which model outputs are compared to the data used to create them (e.g. Chapter 6), and a model corroboration process, in which model outputs are compared against an independent dataset not used at all during the model development and verification stages (Augusiak *et al.*, 2014; Grimm *et al.*, 2014). During model output verification, the model is 'tweaked' to improve its ability to reproduce the patterns seen in the real fishery data, through model selection, parameter calibration, or submodel modification (Chapter 6, Grimm *et al.*, 2014). It is therefore simpler, and more likely, for a model to reproduce patterns in known data used during model development, but if a model can reproduce patterns in independent data, it can provide more confidence that the model is mechanistically correct (i.e. it is not "doing the right thing for the wrong reason") (Augusiak *et al.*, 2014; Grimm *et al.*, 2014). Comparing models against previously unknown independent data is often not possible though, as such data is often not available. For example, if a model is developed to predict the impacts of climate change, independent data for output corroboration are often not available (Grimm *et al.*, 2014). This does not prevent models from being useful (Augusiak *et al.*, 2014), but output corroboration can be considered a 'gold standard' of model validation (Grimm *et al.*, 2014). Documenting the model output corroboration process can provide further evidence of a models reliability, alongside model output verification (Chapter 6). How closely the model output needs to match the independent data depends on the model's purpose.

7.2.4. Aims and Objectives

There were two aims of this Chapter: to present a model output corroboration of an IBM of the Isle of Man scallop fishery; and to demonstrate the potential use of the model for exploring the likely impact of management using hypothetical area closures. The specific objectives were to: 1) Compare model output with real fishery data from the 2013/14 fishing season, which was independent data was not used in the model development; 2) Compare model output with real fishery data from the 2014/15 fishing season, during which a series of new area closures were implemented, providing fully independent data from a novel scenario unknown at the time of model development; and 3) present model output from a series of hypothetical area closures demonstrating the range of impacts on the fishing footprint, scallop catches, and fuel costs.

7.3. Methods

7.3.1. The Isle of Man Scallop Fishery

The Isle of Man (IOM) government has jurisdiction of the management of its 12nm territorial Sea, and there is full Vessel Monitoring System (VMS) coverage of vessels fishing for scallops in this area. Management of the scallop fisheries are updated regularly according to the yearly scallop surveys, and the responses to, and impacts of, these management actions have also consequently been documented by the VMS and logbook data. It therefore represents a data rich system in which to develop and comprehensively validate an IBM.

Since 2014 there have been a series of area closures established in the Isle of Man to protect the *Aequipecten opercularis* (queen scallop) stock from fishing (Figure 7.1). Some of these areas also remained closed to the *Pecten maximus* (king scallop) fishery. Area closures can be a controversial management measure, as it can be difficult to reach a compromise between protecting enough of the higher density areas of stocks and leaving enough profitable fishing grounds open to fishers. In addition, just before the king scallop fishing season started in November 2014, high levels of domoic acid, which exceeded the safe limit of 20 milligrams per kg (EC, 2004), were detected in samples from the Isle of Man. Domoic acid is a toxin that causes amnesiac shellfish poisoning (ASP), which poses a serious risk to human health (Quilliam and Wright, 1989; Wright and Quilliam, 1995). In November and December 2014, areas of the Irish Sea were therefore closed to king scallop fishing until domoic acid levels reduced to safe levels (Figure 7.1).
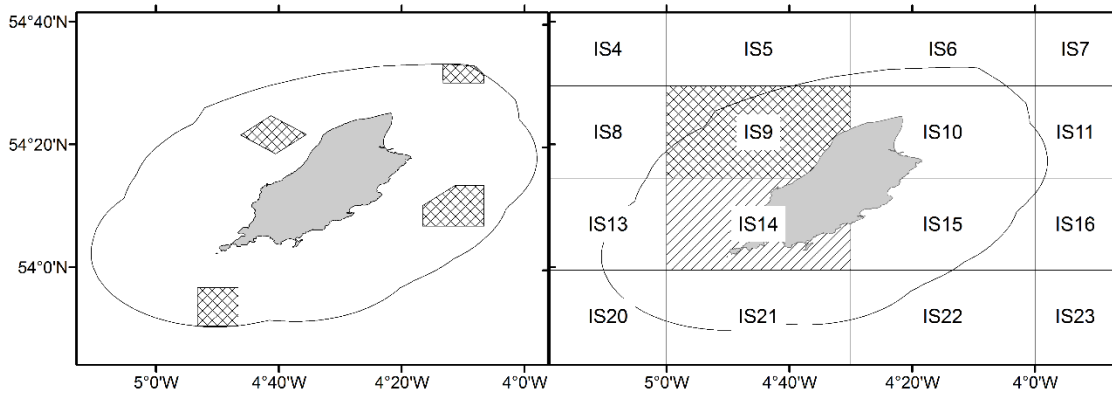
Figure 7.1. A) Areas closed during the queen scallop fishing season in 2014. B) Areas closed due to high levels of domoic acid in 2014. Area IS9 was closed in both November and December 2014, area IS14 was closed during December only.

7.3.2. Model Output Corroboration

An individual-based model was developed in NetLogo, to predict fishing activity in the Isle of Man king scallop fishery (Chapter 5 & 6). The model only predicted activity during the more valuable king scallop fishing season, therefore king scallops are hereon referred to as 'scallops'. Questionnaire data collected in 2013 (Chapter 2), and vessel monitoring system and logbook data from the fishing seasons in 2011- 2013 (Nov – May) were used to develop the model, including providing the data against which model output verification was completed (Chapter 3). In the first stage of model validation, model output verification, the final model generated reasonably accurate output compared to the 2012/13 real fishery data (Chapter 6). In the second stage of model validation, model output corroboration, model output is compared against independent data unknown at the time of model development, which can provide stronger evidence that a model is structurally realistic, and that it is not predicting the patterns correctly but through incorrect mechanisms (Grimm *et al.*, 2014).

The model was used to simulate fishing activity in the 2013/14 (Nov 2013 – May 2014) season, to compare the outputs against an open fishery with no new closures, but with data not used during the development stage. Recreating the fishing activity seen in 2013/14 would add to the weight of evidence suggesting that the model is realistic.

The model was also then used to simulate fishing activity in the 2014/2015 (Nov 2014 – May 2015) fishing season. In this season there were a series of new area closures; this data therefore

represents independent data with novel scenarios that were not part of the model development. If the model re-created the response of fishers to these closed areas, it would provide strong evidence that the model structure is mechanistically realistic (Grimm *et al.*, 2014).

The real closed areas could not be exactly spatially matched to the grid used in the IBM, due to varying projections and the spatial scale of the grid, but a close approximation was achieved with simplified representations (Figure 7.2). In the IBM, vessels chose where to fish at the start of a fishing trip from a set of 'possible patches' that met certain criteria such as being within a maximum distance to shore, being within the 12nm Sea, and being over a fishing ground (Chapter 5). In addition, in the 2014/15 model, additional criteria were added that specified a 'possible patch' must not be closed to fishing for management reasons, or temporarily closed due to domoic acid. The areas closed due to toxins re-opened in January 2015, after which fishers were permitted to fish in these areas.
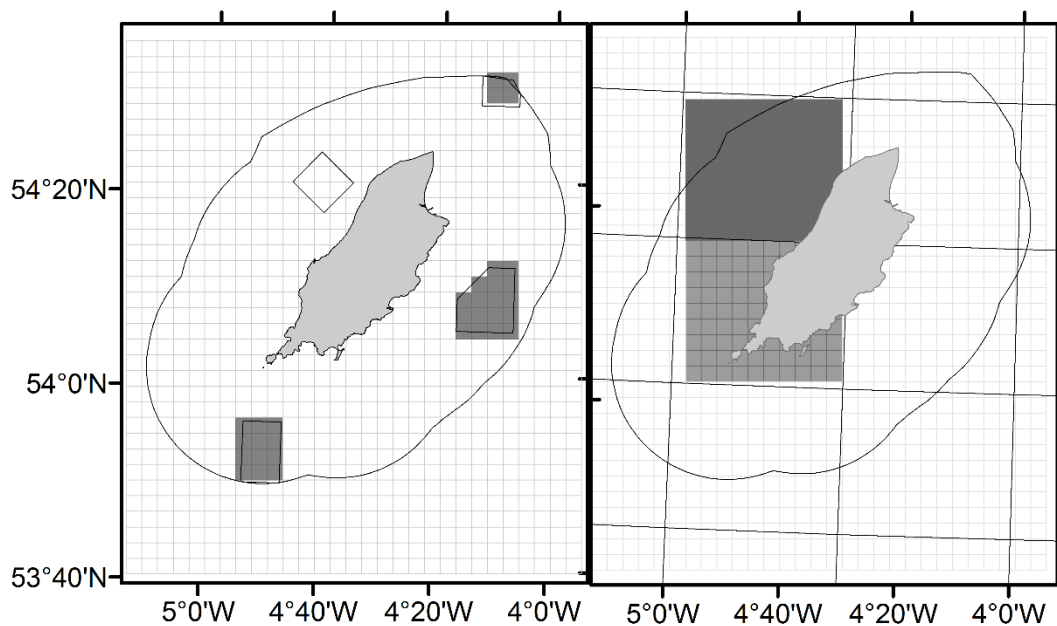
Figure 7.2. Area closures translated to the model grid. A) Areas closed during the queen scallop fishing season (grey polygon outlines), which remained closed during the king scallop season (grey fill). B) Areas closed due to domoic acid toxins (grey outline), closed during November and December 2014 (dark grey fill) and closed during only December 2014 (light grey fill).

7.3.3. Hypothetical Closed Areas

Seven hypothetical closed area model scenarios, intended as illustrations rather than proposals, were then compared to an 'open' fishery model simulation (Figure 7.3). All scenarios protected between 10-30% of stocks (Table 7.1) but in different ways, for example, scenario A, C, and E, all protected about 20% of the scallop stocks, but A closed a high density main ground area, C closed the 3nm area, and E closed lower scallop density less fished areas. These arrangements of closed areas were selected to demonstrate the potential of using different approaches to achieve similar objectives (i.e. closing small high density areas, or large low density areas). Using the model in this way it was possible to explore at how different arrangements of closures could protect different amounts of stock whilst having a different impact on fishers and different realised reductions in catches. These hypothetical closed area scenarios demonstrated what could be done with the model, but the next steps would be to ask fishers and managers from the Isle of Man to propose closed areas which can then be simulated with the model.

Table 7.1. Characteristics of the closed area scenarios

	% of 12nm closed	% scallop biomass in 12nm protected	% study area closed	% scallop biomass protected
A	3.8	21.7	2.1	17.0
B	1.3	10.2	0.7	8.0
C	20.0	21.1	11.3	16.5
D	3.1	14.8	1.7	11.6
E	49.1	19.4	27.8	15.2
F	52.1	29.6	29.4	23.2
G	16.4	11.0	9.2	8.6
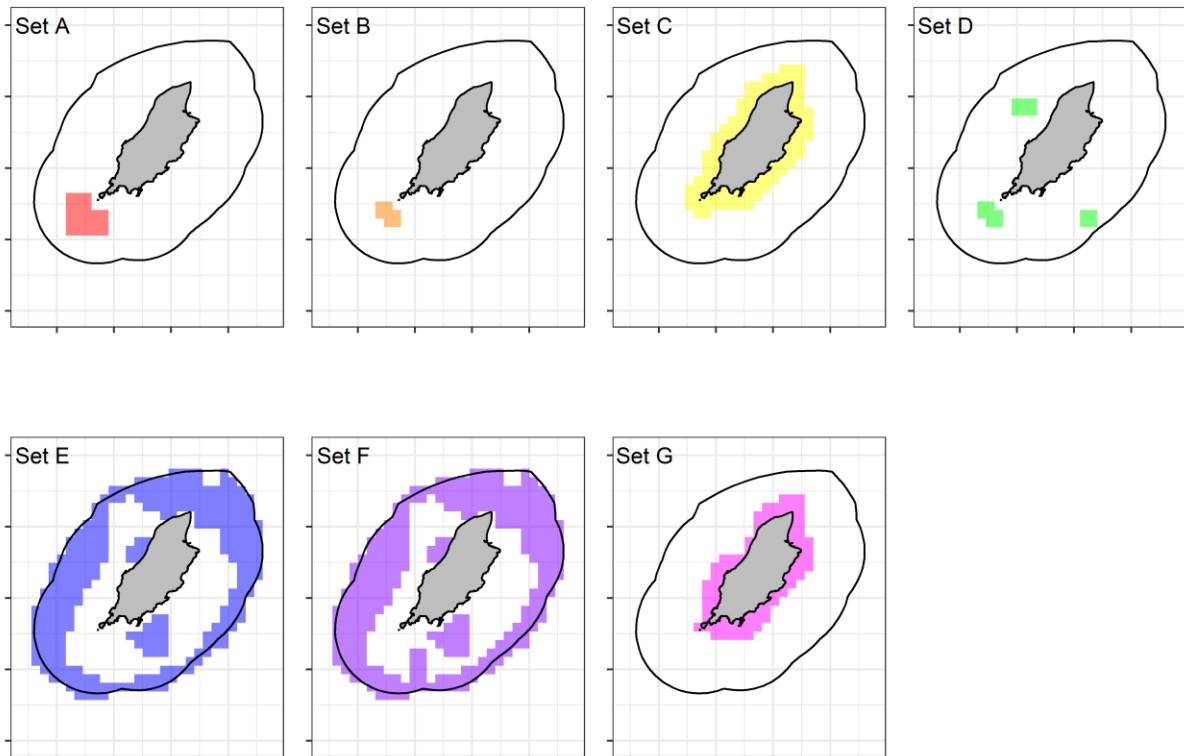
Figure 7.3. Hypothetical closed area scenarios simulated in the model. All scenarios protected between 10-30% of stocks but in different ways, for example, scenario A, C, and E, all protected about 20% of the scallop stocks, but A closed a high density main ground area, C closed the 3nm area, and E closed lower scallop density less fished areas.

7.3.4. Model Settings

There was no single 'best' model identified during model selection (Chapter 6), therefore all 54 accepted models (the top performing 1% of models, which constituted 23 unique model structures, Table 7.2), were taken forward to the model output corroboration, and to explore the potential impact of a series of hypothetical area closures. At the start of the 2013/14 and 2014/15 fishing seasons the starting biomass was updated to represent the same percentage decrease in biomass from the scallop surveys from 2012 to 2013, and from 2013 to 2014 respectively.

Table 7.2. Model settings used to simulate fishing activity in the 2013/14 and 2014/15 fishing seasons, and to simulate the responses to a series of hypothetical area closures.

Initial Patch Choice	Between patch Choice	Return Decision	% random	Accepted runs
Random	Highest	At curfew	0	1
Random	Above average	At curfew	0	8
Random	Above average	Max fishing time	0	4
Above average	Highest	After good takings	0.5	1
Above average	Above average	After good takings	0.5	1
Catch cost ratio	Highest	After good takings	0.5	1
Catch cost ratio	Above average	At curfew	0.5	3
Catch cost ratio	Above average	Max fishing time	0.5	2
Previous effort	Highest	After good takings	0.5	1
Previous effort	Above average	At curfew	0.5	1
Previous effort	Catch cost ratio	Min viable gross	0.5	1
Above average conjoint	Highest	At curfew	0.5	2
Above average conjoint	Highest	After good takings	0	2
Above average conjoint	Highest	After good takings	0.5	3
Above average conjoint	50:50 random:highest	After good takings	0	1
Above average conjoint	Above average	At curfew	0.5	6
Above average conjoint	Above average	Max fishing time	0.5	4
Above average conjoint	Above average	Min viable gross	0.5	1
Above average conjoint	Catch cost ratio	At curfew	0.5	3
Above average conjoint	Catch cost ratio	Max fishing time	0.5	1
Above average conjoint	Catch cost ratio	Min viable gross	0.5	2
Above average conjoint	Catch cost ratio	After good takings	0	3
Above average conjoint	Catch cost ratio	After good takings	0.5	2

7.3.5. Data Analysis

The analysis is split into two parts. In Part 1, a model output corroboration is presented. Model output data from the three simulated years were compared against the real fishery logbook records from the 2012/13, 2013/14, and 2014/15 fishing seasons. There were three levels to output corroboration; whether the model could predict realistic values for the two new seasons; whether it could predict the correct magnitude of change from year to year, but not necessarily the correct values; and at the simplest form, whether it could predict the right direction of change (i.e. simple increase or decrease). Model outputs from 2012/13 were used as a baseline for comparison with the 2013/14 model outputs, to determine the magnitude of change captured with the model, to account for discrepancies between the 2012/13 model output and real values. Initially all model structures were considered together, and then the performance of different model structures was also explored to provide insights into submodel performance. For simplicity, in the text, '2012' refers to the fishing season starting in 2012 (Nov 2012 – May 2013), '2013' refers to the fishing season

starting in 2013 (Nov 2013 – May 2014), and '2014' refers to the fishing season starting in 2014 (Nov 2014 – May 2015).

In part 2 model outputs from a series of hypothetical closed areas were analysed. In these scenarios, outputs of all of the model structures were averaged to obtain a likely outcome. An analysis of variance (ANOVA) test was performed in R (R Development Core Team, 2016) to determine if the closed area scenarios simulated significantly different values to the open fishery simulations. The outcome of each individual model structure was also explored, to provide insights into model performance and whether particular submodels predicted different outcomes. Outputs were visualised in figures that clearly indicated if there was a positive or negative impact on fishers and the environment (measured by changes to the fishing extent/footprint, catches, and fuel use).

7.4. Results

7.4.1. Part 1: Comparing overall model outputs from 2013 and 2014

The model recreated realistic values for the fishing extent in both 2013 and 2014 (Figure 7.4). Whilst the extent value in 2013 was realistic, the increase in extent from 2012 to 2013 was too high, because the model under predicted the extent slightly in 2012. The model captured both the value and the magnitude of decrease in extent from 2013 to 2014 following the establishment of the closed areas.

In the real fishery the average CPUE over the years remained relatively constant, with a slightly lower value in 2013. The model predicted a slight decrease in CPUE from 2012 to 2013, but the magnitude of the prediction was larger than in reality. The model predicted a further decrease in CPUE from 2013 to 2014, which was not the case in the real fishery. The fuel use was relatively constant across each season in both reality and the models, although the model slightly overestimated the values.

The average landings remained constant between 2012 and 2013 in the real fishery, with a decrease in 2014. The model incorrectly predicted a decrease in average landings from 2012 to 2013, but correctly captured a decrease in landings from 2013 to 2014, although the magnitude of decrease was larger than reality. The model predicted average landings lower than reality in both 2013 and 2014, although the values in the highest range of predictions in 2013 were realistic.

The total landings decreased year on year in the fishery, which was a trend captured by the model. However, the predicted magnitude of decrease each year was too large. From 2012 to 2013 the

catches reduced by about 60% in the model, approximately the same proportion by which the starting biomass was reduced.
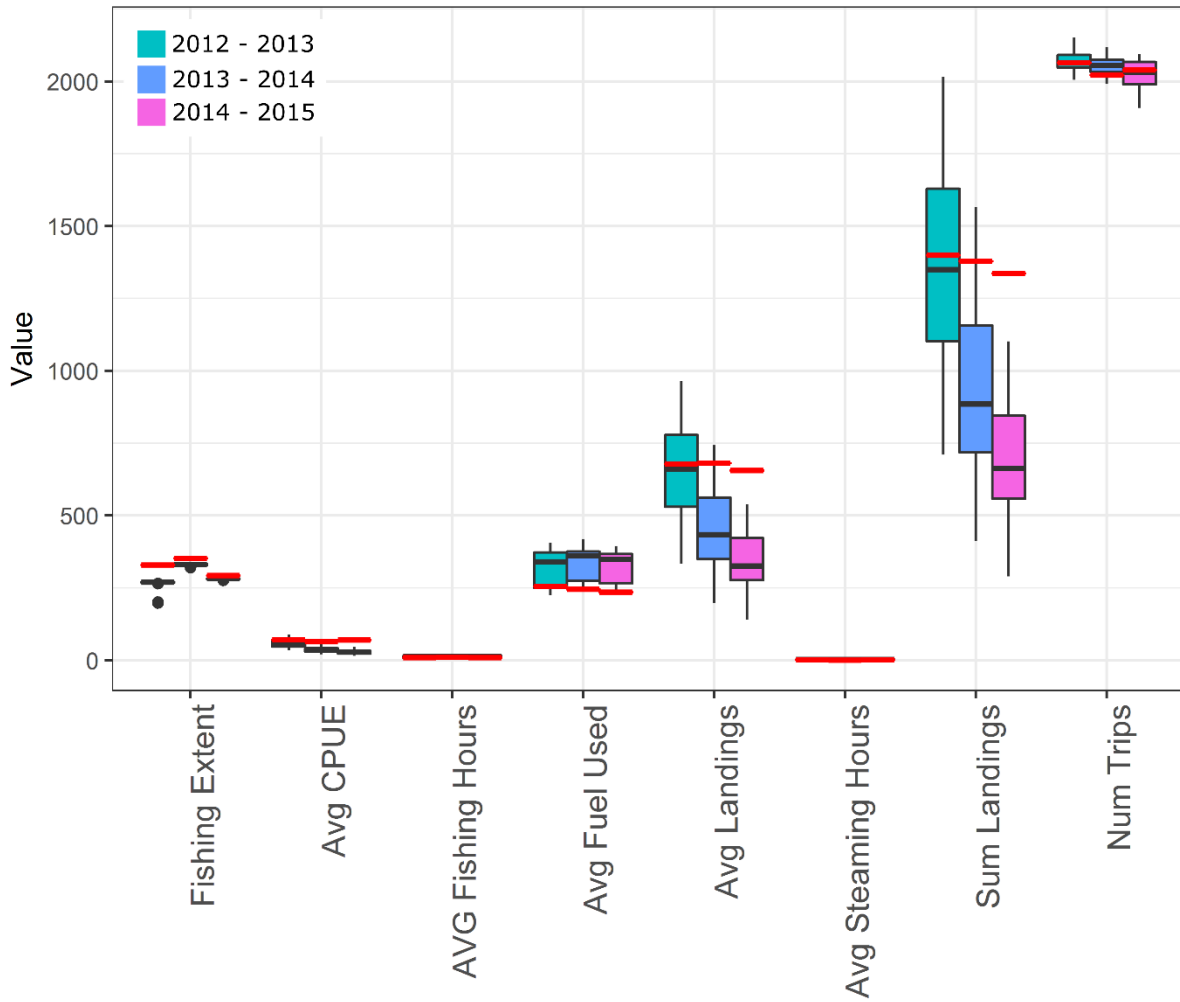
Figure 7.4. Average (or sum) values from each model output from 2012/13, 2013/14, and 2014/15, compared against the average (or sum) values in the real fishery data values (red lines)

7.4.2. Part 1: Comparing the monthly trend in model outputs from 2013 and 2014

The total catch was reproduced well at the start of 2013, but towards the end of the season the landings per month were too low (Figure 7.5). In 2014 the trend in total catches was reasonably realistic, but the magnitude was consistently too low. The trend in average catch per month, and average CPUE per month was captured relatively well by the model in 2014, but the values were too low. The monthly average catches and CPUE were variable in the real fishery, with no clear increasing or decreasing trend. The model predicted a decrease in these values throughout the season.

The average hours fishing, the average time steaming, and the average fuel use were all overestimated by the model, but the variation between months and between the model and real values were relatively low. The number of tows completed per ground was relatively accurate in each year, but the landings per ground was less accurate in 2013 (Figure 7.5).
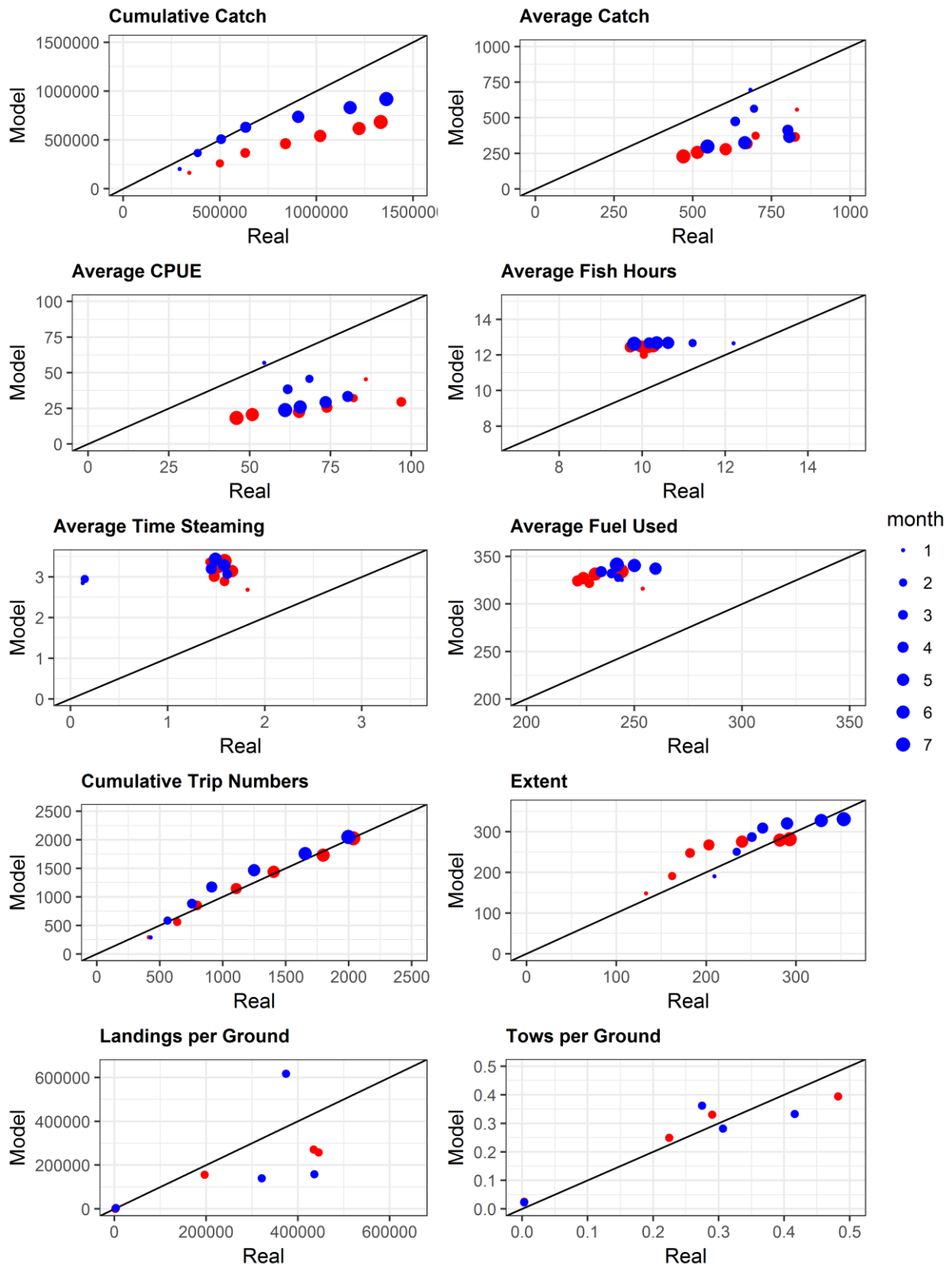
Figure 7.5 Monthly fishery values versus the model outputs, from 2013 (blue) and 2014 (red). Points increase in size as the season progresses.

7.4.3. Part 1: Comparing the magnitude of change in model outputs from 2013 and 2014, for different behavioural submodels

How close the model outputs were to the real fishery values depended on which model structure was used (Figure 7.6). In 2013, realistic values for the average landings and total landings were generated when using a patch choice decision in which fishers evaluated the catch:cost ratio of a patch (i.e. chose a patch with the highest ratio between the expected catch rate and the travel cost). The values generated for the average landings and the total landings were also more realistic when fishers returned to port at curfew or after the maximum time they would be willing to fish for. The fuel use was more accurate when vessels returned to port at a catch that they considered had achieved a threshold value such as a minimum viable catch or what they considered 'good takings'.
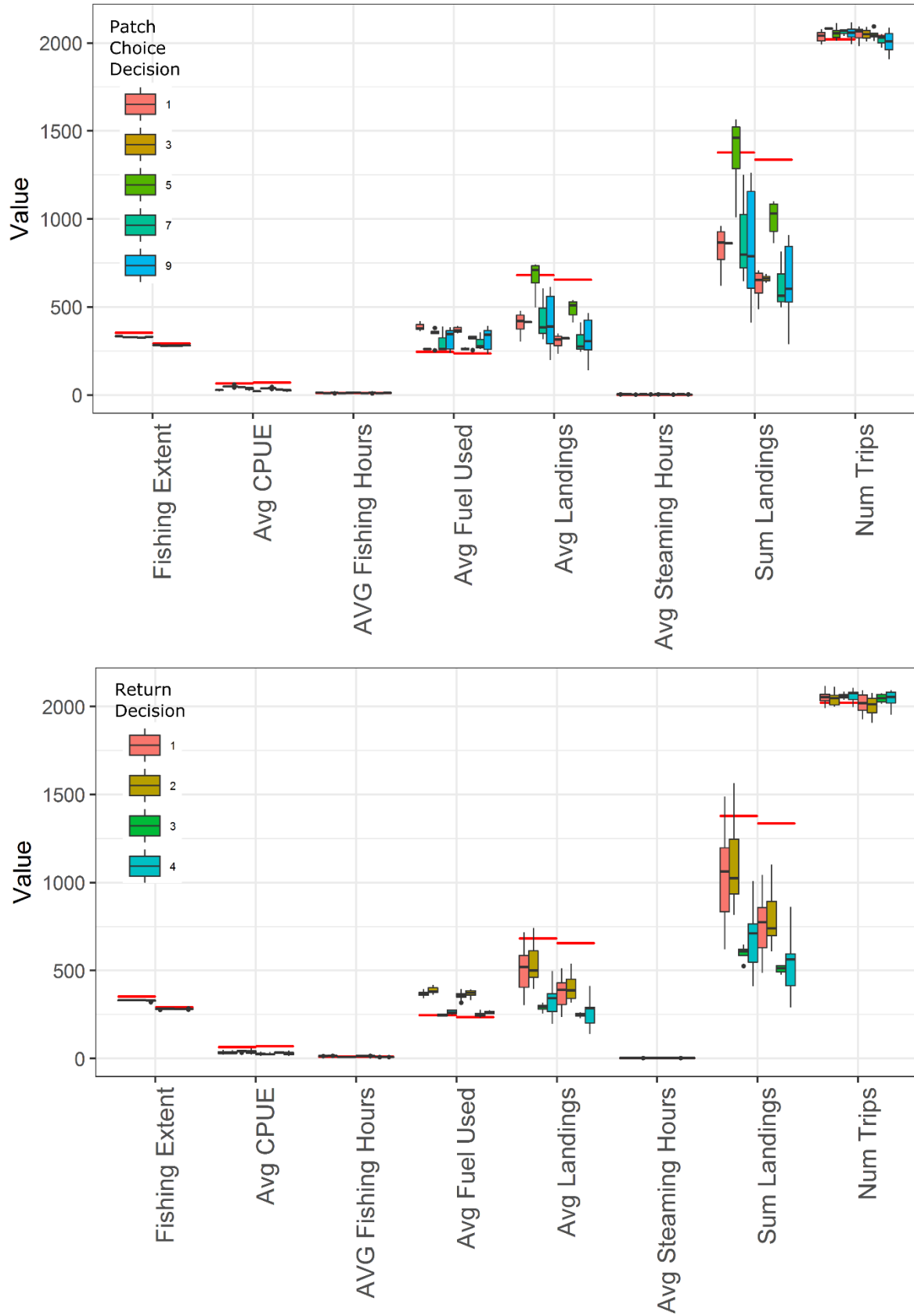
Figure 7.6 Model outputs from 2013 and 2014 coloured according to the patch choice decision rule and return to port decision rule

The magnitude of change in mean hours fishing, mean hours steaming, fishing extent, and mean fuel used were fairly realistic. Nevertheless, the model predicted a slightly smaller reduction in extent than in reality. Models in which fishers chose where to fish by evaluating the catch:cost ratio of a patch (i.e. chose a patch with the highest ratio between the expected catch rate and the travel cost) most substantially overestimated the reduction in landings from 2013 to 2014. The overall magnitude of change from before and after the closures was best captured using models in which fishers returned to port after a minimum viable catch had been achieved, and when fishers chose a patch with above average expected catch rates or above average utility. Therefore, the absolute values were best reproduced when using a return to port decision based on fishing for as long as permitted or as long as fishers were willing (Figure 7.6), but the magnitude of change was best reproduced when returning to port once a threshold value had been achieved (a minimum viable catch or a 'good' catch) (Figure 7.7).
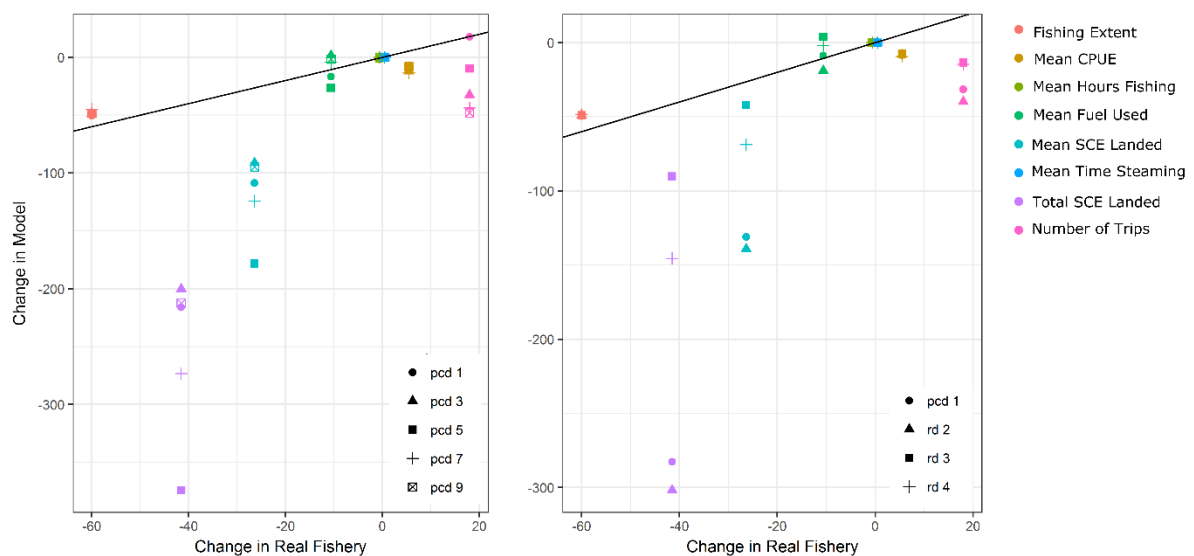
Figure 7.7. The magnitude of change between model output values in 2013 and 2014 in response to area closures.

7.4.4. Part 2: Simulating hypothetical closed area scenarios

Model output from the hypothetical closed area scenarios were compared against model output from simulations with no closed areas. Scenario A, C, and E, all protected about 20% of the scallop biomass inside the 12nm Sea, but their predicted impacts were different (Table 7.3; Figure 7.8). In scenario A, one high density area of scallops was closed to fishing; the model predicted that there would be no significant impact on the fishers' landings, and a relatively small reduction in extent. In scenario C, the 3nm Sea was closed to fishing, leading to a large reduction in extent, but the model predicted it would lead to a significant reduction in landings and CPUE, and a significant increase in fuel use, which would therefore have an impact on fishers economically. In scenario E, the lowest scallop density areas were closed to fishing, therefore a much larger area of the seabed was closed to fishing to protect 20% of the biomass, however the model predicted a significant increase in landings and CPUE and a decrease in fuel use. This demonstrates how the spatial arrangement of closed areas could substantially alter the impacts of management.

Table 7.3. Closed Area Scenarios

	% of 12nm closed	% scallop biomass in 12nm protected	% study area closed	% scallop biomass protected	% reduction in scallop catch	% red in extent
A	3.8	21.7	2.1	17.0	10.0	6.6
B	1.3	10.2	0.7	8.0	4.1	2.2
C	20.0	21.1	11.3	16.5	1.1	21.0
D	3.1	14.8	1.7	11.6	7.3	5.4
E	49.1	19.4	27.8	15.2	6.1	35.0
F	52.1	29.6	29.4	23.2	0.1	39.7
G	16.4	11.0	9.2	8.6	3.8	15.3
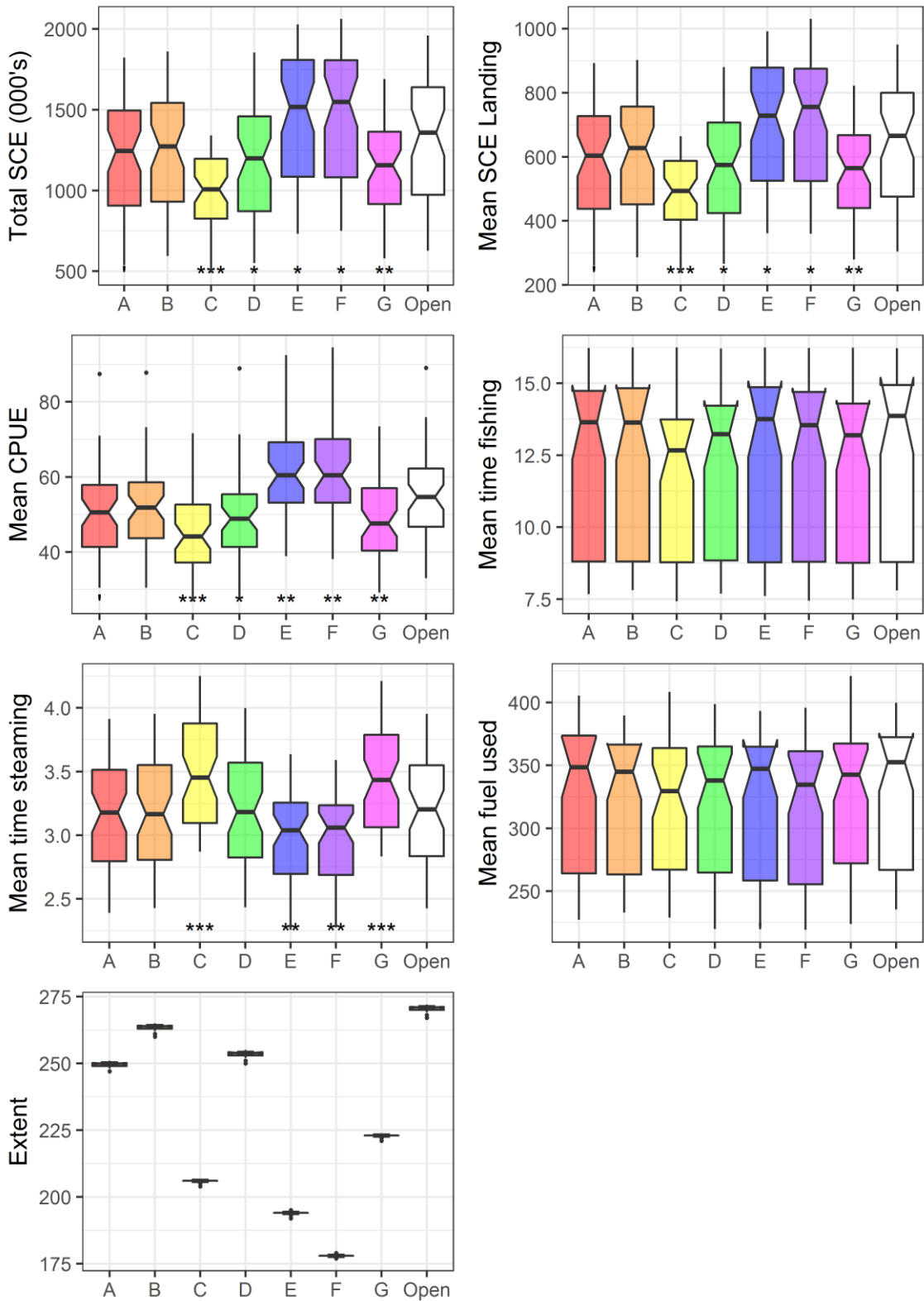
Figure 7.8. Comparison of closed area model simulations with open (i.e. no closed area) model simulations. Asterix indicate the significant significant of an ANOVA test between each closed area scenario and the open simulations. *** indicates significance at the 0.001 level, ** indicates significance at the 0.01 level, and * indicates significance at the 0.05 level.
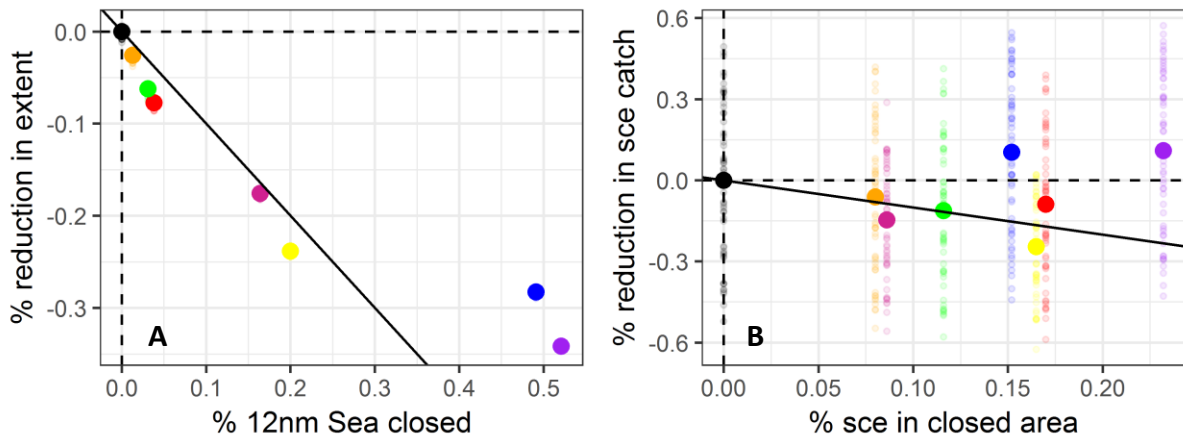
Figure 7.9. A) Comparison of % of 12nm Sea closed vs reduction in fishing footprint. B) Comparison of % scallop biomass contained in closed areas and % reduction in scallop biomass caught.

The area of seabed closed to fishing correlated relatively well with the % reduction in extent, but there was some deviation (Figure 7.9a). There is possibly a non-linear relationship between the % of the seabed closed and the reduction in extent, i.e. closing more than a certain amount of area may cease to be useful for reducing the fishing footprint. The % of scallops that were contained in closed areas was not well correlated with the % reduction in scallops caught (Figure 7.9b). The scenarios in which the low density areas of scallops were closed to fishing, or the areas close to shore were closed to fishing, did not correlate at all with the % of scallop biomass in closed areas. This could be considered positive or negative depending on the desired outcome; a certain % of scallops and habitat has been protected, without reducing the catches available to fishers, but, the overall pressure on the total population has not been reduced. This outcome is to be as expected, as the high density areas of scallops remained open to fishing, so unless effort had also been limited in some other manner, the overall catches would likely be maintained.
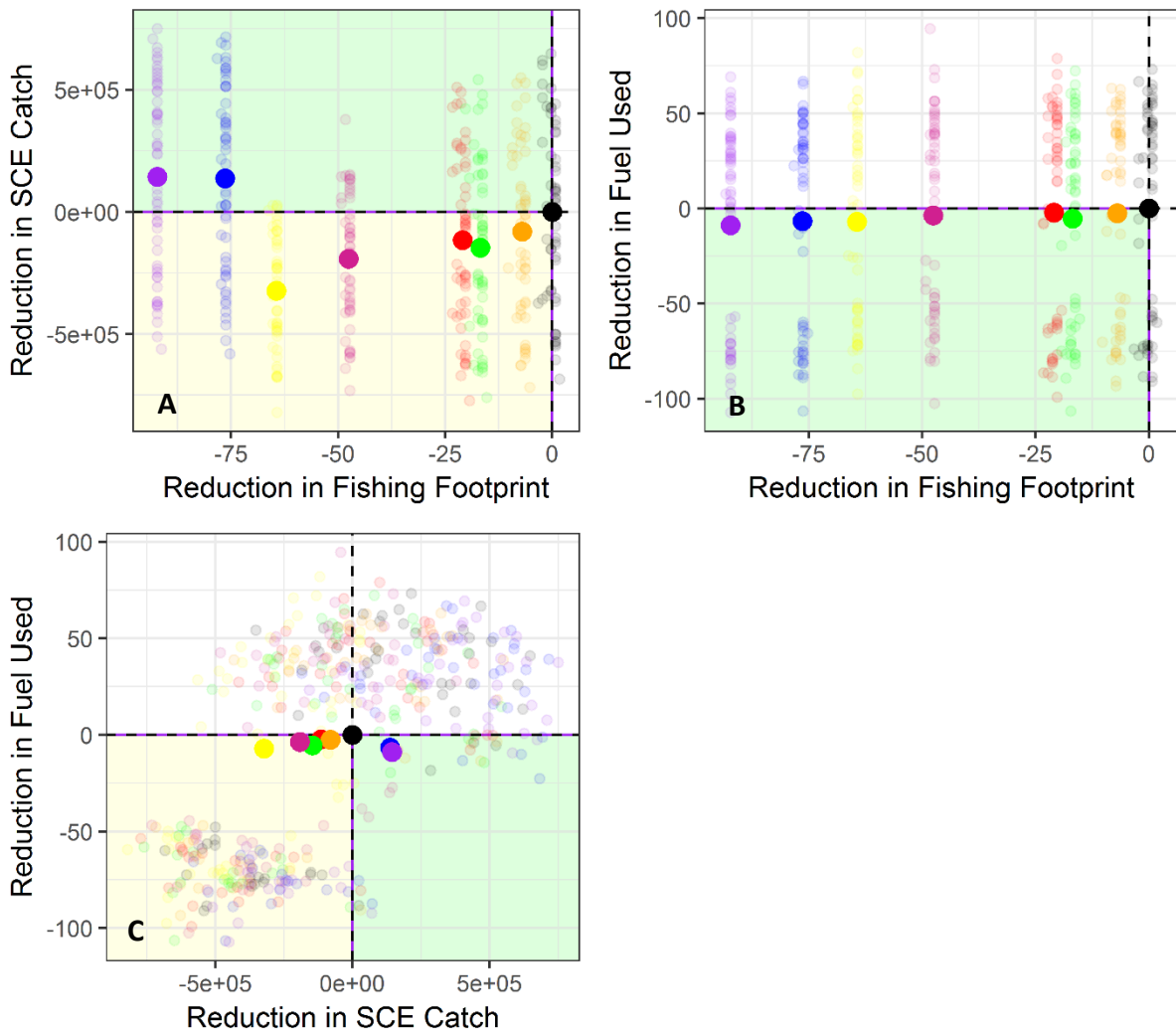
Figure 7.10. Comparing the reduction in scallop catch, fishing footprint, and fuel use, to determine which closed areas have a positive or negative impact on the environment and/or fishermen. Green areas = most positive impact on fishermen. Yellow areas = most positive impact on environment/stocks.

The reduction in fishing footprint was not well correlated with the reduction in scallops caught; i.e. large closed areas did not necessarily mean large reductions in catches. In fact, the model suggested a possible increase in scallop catches with two closed scenarios (E and F, blue and purple), because it restricted activity to only the highest density areas therefore preventing fishing over less productive grounds. There was also little correlation between the reduction in fuel used and the reduction in fishing footprint, and between the reduction in the scallop catch and the reduction in fuel.

Green areas indicated model simulations that could have a positive impact on fishermen (i.e. there was an increase in catches, or a decrease in fuel usage). Yellow areas indicate model simulations that could have a positive impact on the environment (i.e. reduce catches, footprint, or fuel use), but

fishermen might not consider as positive (i.e. reduction in catches). Scenario E appears to be the most agreeable solution for fishermen because it could lead to an increase in catches through restricting activity, and only previously lightly fished areas were closed. Scenario F could also be agreeable to fishermen, and may be a more preferable solution for managers, as it protected more scallop biomass, and included a small area of high density scallops. Nevertheless, closing such a large area to fishing could be controversial, even if it consisted of low density scallop areas.

7.4.5. Uncertainty in Simulated Closed Area Outcomes

Whilst the reduction in fishing footprint was relatively consistent within each hypothetical closed area scenario, the changes in catches and fuel use were considerably more variable, including for the open model simulations (Figure 7.11). For example, although the average outcome of scenario E (blue) was in the green positive impacts area (Figure 7.11), the individual model outputs were variable, with some in the yellow area suggesting a reduction in catches, and some in the top right quadrant suggesting an increase in fuel use. Nevertheless for scenario C and G the model did more consistently predict a reduction in catches, therefore could be considrered more likely to have a negative impact on fishers. Using a range of models may simulate the range of likely impacts, accounting for the high variation and uncertainty in the system.

The model outputs appear to be consistently clustered into two groups according to their return to port decision (Figure 7.11). When returning to port at curfew or at the maximum fishing time the closed areas were less likely to lead to a reduction in catches. It may therefore be possible for vessels to compensate for reductions in catches by fishing for longer.
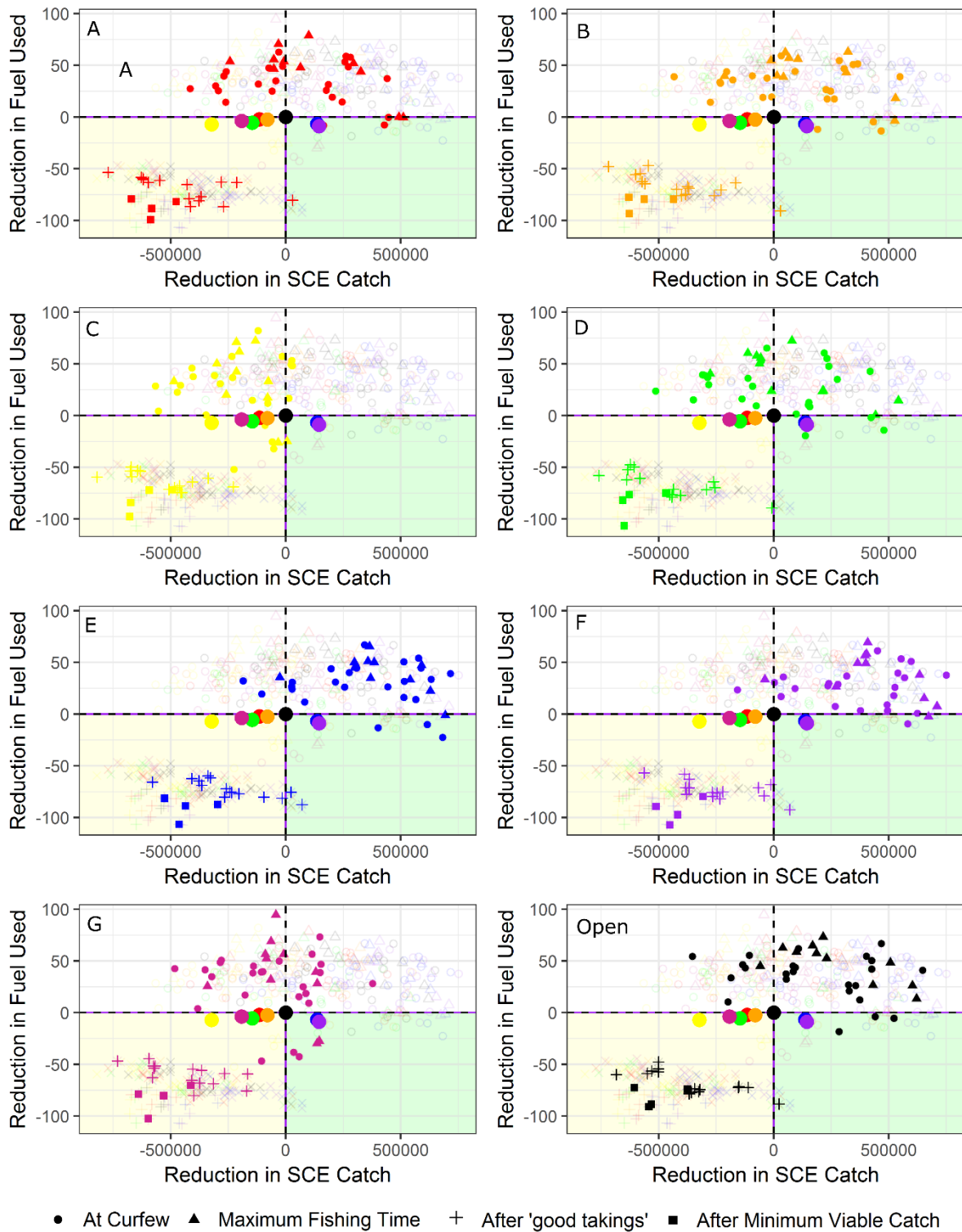
Figure 7.11. Comparing the reduction in scallop catch and fuel use for each closed area scenario, and highlighting the variability in model predictions when different return to port decision rules were used. Green areas = most positive impact on fishermen. Yellow areas = most positive impact on environment/stocks.

7.5. Discussion

Model output corroboration, that is testing model simulations against independent data not used during model development, is an important part of model validation that provides additional weight to a model validation (Grimm *et al.*, 2014). This IBM of the Isle of Man scallop fishery was able to reproduce some patterns in the independent data, but not others, leading to further hypotheses for model development and validation. Comparing model output from hypothetical closed area scenarios demonstrated the potential application of the model.

7.5.1. Model Output Corroboration – How did the model perform?

There are two aspects of comparing model output data to the real fishery data; whether the absolute values are realistic, and whether the trends are realistic. If a model can reproduce trends and patterns well, but the magnitude of values is not accurate, model calibration may help to improve the model fit. However, if the trends are wrong, this can suggest that the model structure requires further development, as the mechanisms have not been adequately captured. The model reproduced realistic values for all variables in 2013 and 2014, aside from the average daily landings and total landings over the season which were too low. In 2013 the scallop landings values at the highest end of model predictions were realistic, but in 2014 all model outputs were too low. The decrease in landings from 2012 to 2013 and from 2013 to 2014 correlated with the amount the starting biomass in the model was reduced by, suggesting that catches in the model were quite sensitive to the starting biomass (Chapter 6). Each year the starting biomass in the model was reduced by a relatively crude scaling factor derived from the stock surveys, from the % change in mean scallop biomass density calculated from the survey points. The survey had relatively low replication, thus estimating a stock decrease in this manner is relatively uncertain. It is, however, a data limitation to the model, as there is no current stock assessment and scientifically estimated total biomass value. A stock assessment methodology is under development for the king scallop fishery; once this is available, further model validation could improve the model fit.

The spatial resolution of the scallop survey was another data limitation, as these values were then interpolated, and average values attributed to each 3km grid cell, which may average out higher densities of scallops within the 3km cells. Fishers may be able to successfully target the higher density scallop areas within a 3km by 3km area, and achieve a higher catch rate than is predicted from the mean scallop biomass values. It may be possible to improve the model fit by increasing/calibrating the gear efficiency parameter, effectively considering it more as a 'catch

efficiency' parameter, accounting more for the spatial distribution of scallops within a grid cell. A final potential source of error is that the model assumes 100% compliance with the regulations; it is feasible that this is not the case and is contributing to an underestimation of catches, although unlikely that it could account for such a magnitude of difference. It is difficult to distinguish the source of inaccuracy in landings, whether there is a structural inaccuracy in the model itself, or an inaccuracy in the scallop biomass and density values (due to either low replication in the survey data or inappropriate treatment of the data). Nevertheless, when a full stock assessment is available, the uncertainty surrounding the stock biomass could be reduced.

7.5.2. How did different model structures perform?

Models in which fishers chose where to fish based on the expected catch to travel cost ratio predicted realistic landings for 2013, and the most realistic (although too low) landings in 2014. Returning to port at curfew or at the maximum time they would be willing to fish for also produced some realistic values for the landings in 2013, and the most realistic values in 2014 following the area closures. However, returning to port after what fishers considered a minimum viable catch produced the most realistic *change* in catches from 2013 to 2014. Choosing an initial patch with an above average expected catch rate, or an above average utility score produced the most realistic changes in catches, whilst using a catch:cost ratio produced the least accurate change in catches. Therefore, the model structures that best reproduced the absolute values were not the model structures that best reproduced the trend or change in catches. Models that better reproduced the change in catches, and thus response to closed areas, could be considered more structurally and mechanistically realistic.

Further model development could include a model selection process comparing the ability of different model structures to predict the change in catches year on year. As a management tool, continual development would be needed, but the model could be updated each year and used to predict the following season. The spatial arrangement of closed areas was slightly altered for the 2015 season, and there were no ASP closures. In the next cycle of model development (Grimm *et al.*, 2014; Grimm and Railsback, 2005), the data for 2013 and 2014 could be used to refine the model through model output verification, and model output corroboration could be performed using the 2015 data.

7.5.3. Simulations of hypothetical closed area scenarios

Simulating the response to hypothetical closed areas demonstrated the potential of the model for informing management decisions. For example, it demonstrated how closing different arrangements of the 12nm Sea to fishing could have quite varying impacts on the fishery. The model predicted that if large areas of low density scallop biomass were closed to fishing it could actually have a positive impact on the fishery, through increasing catches and protecting a large amount of the seabed. These low density scallop areas were subject to very low, or no fishing pressure, which could be for several reasons. There may be no scallops in these areas, or there may be obstructions or environmental features that make fishing in these areas dangerous or difficult, but the seabed may still be of environmental value and it could potentially be protected with little impact to the fishers. The increase in catches associated with these scenarios agreed with what has been seen in a closed area in Ramsey Bay (Northeast tip of Isle of Man). When fishers were directed to this high scallop density, closed area, the catch rates were substantially higher than in the open fishery, allowing fishers to be much more efficient (Isobel Bloor, pers. comms.). In the first year that fishing was permitted in Ramsey Bay a single vessel did the fishing and takings were shared amongst all vessels; the catch rates were high enough, and the catch limit strict enough, that this provided the most economical way to fish the area. Nevertheless, in subsequent years, the fishers requested that more vessels be allowed to fish in this area, and subsequently the overall efficiency was lower. Fishing is a lifestyle, the competitive nature of fishers, and the 'thrill of the chase' should not be underestimated (Pollnac and Poggie, 2008); fishers may thus be opposed to closing such large areas of the seabed, effectively directing vessels to the more economical grounds.

There may be conflicting interests when designing area closures, depending on whether they are created as a stock management or a conservation tool. To conserve biodiversity, closing areas that have not already been heavily fished may be preferable, however for stock management and to reduce the amount of scallops caught it may be necessary to close higher density areas, which could have the unintended impact of displacing effort to previously unfished areas (Nilsson and Ziegler, 2007). To gain the most benefit from the model simulations, clearly defined objectives would be needed. For example, is the aim to reduce the fishing footprint, to minimise the total scallops removed from the sea, or to protect a certain amount of the seabed / stock whilst minimising the impact on fishers? Using a simulation tool it might also be possible to consider other objectives such as improving the fuel efficiency (Bastardie *et al.*, 2013). In addition, the uncertainty surrounding simulations could be considered, for example, fishers may prefer a management option that has lower uncertainty, over one that might bring more substantial benefits, but also has a chance of more substantial losses (Eggert and Martinsson, 2004). The next steps would be for fishers and

managers in the Isle of Man to propose closed area scenarios that they would like simulating with the model, and to determine the objectives of the management.

7.5.4. Lessons Learnt During Model Validation

Model validation is not a binary criterion, which a model either passes or fails at the end of its development (Augusiak *et al.*, 2014). A model is always a simplification of reality, and is therefore never a perfect representation of a system; the usefulness and credibility of a model can only be built on over time (Augusiak *et al.*, 2014; Grimm *et al.*, 2014). In a fishery with VMS and logbook data, new data on fishing activity will be continually generated, with which an IBM could be continually refined. Just as stock assessment methodologies have progressed and evolved to become more complex and realistic, fishery IBMs will need to be continually developed and measured against real fishery data to refine the behavioural models underpinning them. It is important that these stages of model development are reported (Augusiak *et al.*, 2014; Grimm *et al.*, 2014), to inform future model development, and so that the model can be applied based on a thorough understanding of its performance, the justification for the final model structure, and the uncertainty in model outputs.

This analysis has demonstrated how different model structures can predict quite different outcomes of management. Fishery systems may be too complex to distil to a single 'accurate' model, but having a suite of models that together give a reasonable representation of the fishery could allow the range of likely impacts to be considered. Used alongside more conventional biological stock models, an IBM such as this may assist decision-makers when considering the range of likely impacts on the fishery. It would, however, be important to effectively communicate the uncertainty to all stakeholders (Cartwright *et al.*, 2016).

In part 1, the results suggested that models in which fishers return to port after a threshold catch may be more mechanistically realistic, as they captured the magnitude of change (i.e. the response) of fishers better. However, in part 2, the reduction in catches following the area closures were less severe when fishers returned to port after the curfew or a maximum possible fishing time. This could be interpreted in 2 ways; modelling fishers as too 'optimal' may underestimate the impacts of management on fishers, or; fishers may be able to change their behaviour to compensate for management restrictions. Modelling fishers as true profit maximisers who will fish for the maximum time permitted may underestimate the impacts of management, by overestimating the likelihood of vessels fishing for longer to compensate. Nevertheless, it also suggests managers should be mindful

of adaptive behaviour. If, under open fishery conditions, the most realistic model structures include behavioural rules in which vessels return to port after a threshold catch, the potential of vessels to simply compensate by fishing for longer should be considered, otherwise the effectiveness of the management may be overestimated. Continual validation and development cycles would be required throughout the models life. There is perhaps a strength to using a range of model structures to simulate the outcome of management, through being able to explore and consider a range of likely outcomes accounting for the range of possible behaviours.

7.6. Conclusions

A full model validation, including a model output verification (Chapter 6) and a model output corroboration, does not guarantee that a model is sufficiently good (Augusiak *et al.*, 2014). It does, however, provide comprehensive information that can be used by decision-makers when evaluating if and how to use a simulation model to aid decision making (Grimm *et al.*, 2014). The degree to which a models output is required to match the real fishery data will depend on the management context and the questions being asked, and appropriate weight and consideration can be given to the model output depending on the level of uncertainty. A fishery management simulation model can only provide guidance to decision-makers, to help explore the potential risks and outcomes of different courses of action. A variety of model structures may help to account for uncertainty in predictions, highlighting the range of possible outcomes, rather than trying to distil such a complex system as a fishery into a single output value.

7.7. Acknowledgements

7.8.   References

Augusiak, J., Van den Brink, P. J., and Grimm, V. 2014. Merging validation and evaluation of ecological models to 'evaludation': A review of terminology and a practical approach. Ecological Modelling, 280: 117–128.

Bastardie, F., Nielsen, J. R., Andersen, B. S., and Eigaard, O. R. 2013. Integrating individual trip planning in energy efficiency – Building decision tree models for Danish fisheries. Fisheries Research, 143: 119–130.

Burgess, M., Drexler, M., Axtell, R., Bailey, R., Watson, J., Ananthanaryanan, A., Cabral, R., *et al.* 2017. The role of agent-based modeling in systems-based fishery management. Fish and Fisheries (In Review).

Cartwright, S. J., Bowgen, K. M., Collop, C., Hyder, K., Nabe-Nielsen, J., Stafford, R., Stillman, R. A., *et al.* 2016. Communicating complex ecological models to non-scientist end users. Ecological Modelling, 338: 51–59.

Daw, T. M. 2008. Spatial distribution of effort by artisanal fishers: Exploring economic factors affecting the lobster fisheries of the Corn Islands, Nicaragua. Fisheries Research, 90: 17–25.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES Journal of Marine Science, 60: 371–380.

EC. 2004. Regulation (EC) No 853/2004 if the European Parliament and of the Council of 29 April 2004.

Eggert, H., and Martinsson, P. 2004. Are commercial fishers risk-lovers? Land Economics, 80: 550–560.

Evans, M. R. 2012. Modelling ecological systems in a changing world. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 181–190.

Evans, M. R., Grimm, V., Johst, K., Knuuttila, T., de Langhe, R., Lessells, C. M., Merz, M., *et al.* 2013. Do simple models lead to generality in ecology? Trends in Ecology & Evolution, 28: 578–83.

Fulton, E. a, Smith, A. D. M., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Grimm, V., Augusiak, J., Focks, A., Frank, B. M., Gabsi, F., Johnston, A. S. A., Liu, C., *et al.* 2014. Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. Ecological Modelling, 280: 129–139.

Grimm, V., and Railsback, S. F. 2005. Individual-Based Modeling and Ecology. Princeton University Press, Princeton.

Hilborn, R. 2007. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Hilborn, R., Fulton, E. A., Green, B. S., Hartmann, K., Tracey, S. R., and Watson, R. A. 2015. When is a fishery sustainable ? Canadian Journal of Fisheries and Aquatic Sciences, 1441: 1–46.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., *et al.* 2004. When can marine reserves improve fisheries management? Ocean & Coastal Management, 47: 197–205.

Jennings, S., Smith, A. D. M., Fulton, E. A., and Smith, D. C. 2014. The ecosystem approach to fisheries: management at the dynamic interface between biodiversity conservation and sustainable use. Annals of the New York Academy of Sciences, 1322: 48–60.

Nilsson, P., and Ziegler, F. 2007. Spatial distribution of fishing effort in relation to seafloor habitats in the Kattegat, a GIS analysis. Aquatic Conservation: Marine and Freshwater Ecosystems, 17: 421–440.

Pascoe, S., and Mardle, S. 2005. Anticipating fisher response to management: Can economics help? ICES Annual Science Conference. Aberdeen.

Plagányi, E. E., Punt, A. E., Hillary, R., Morello, E.B., Thébaud, O., Hutton T., Pillans, R. D., Thorson, J. T., Fulton, E. A., Smith, A. D. M., Smith, F., Bayliss, P., Haywood, M., Lyne, V., Rothlisberg, P.C. 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries, 15 (1): 1 – 22.

Pollnac, R. B., and Poggie, J. J. 2008. Happiness, well-being and psychocultural adaptation to the stresses associated with marine fishing. Human Ecology Review, 15: 194–200.

Quilliam, M. A., and Wright, J. L. C. 1989. The amnesic shellfish poisoning mystery. Analytical Chemistry, 61: 1053–1060.

R Development Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/.

Railsback, S. F., and Johnson, M. D. 2011. Pattern-oriented modelling of bird foraging and pest control in coffee farms. Ecological Modelling, 222: 3305–3319.

Rykiel, E. J. 1996. Testing ecological models: the meaning of validation. Ecological Modelling, 90: 229–244.

van der Vaart, E., Beaumont, M. A., Johnston, A. S. A., and Sibly, R. M. 2015. Calibration and evaluation of individual-based models using Approximate Bayesian Computation. Ecological Modelling, 312: 182–190.

Wright, J. L. C., and Quilliam, M. A. 1995. Methods for domoic acid, the amnesic shellfish poisons. *In* Manual on Harmful Marine Microalgae. IOC, Manuals and Guides 33., pp. 114–116. Ed. by G. M. Hallegraef, D. M. Anderson, and A. D. Cembella. UNESCO, France.

CHAPTER 8: GENERAL DISCUSSION

Fisher behaviour is an area of considerable uncertainty in fisheries management, and both our understanding of it, and the translation of this understanding into predictive management tools, is underdeveloped (Fulton *et al.*, 2011; Hilborn, 2007; van Putten *et al.*, 2012). Throughout this thesis I have presented a range of research into fisher behaviour, relating to the title "Developing a spatially dynamic model to evaluate management scenarios in the Isle of Man scallop fishery". Each chapter built on the previous, towards the development of an individual-based model (IBM) of the Isle of Man scallop fishery. The IBM presented was spatially explicit, dynamic, and provided the capacity to evaluate the likely impact of different management strategies in terms of the change in fishing footprint, scallop catches, and fuel costs. The research presented in each chapter has significance for one or more of three main themes; *understanding fisher behaviour*, *modelling fishing activity*; and *predicting outcomes of management* (Figure 8.1). These three themes are not mutually exclusive, but represent a feedback system through which continual advancement in our understanding may improve our ability to predict the outcome of management. Increasing our knowledge and understanding in all three of these areas could help inform fisheries management and help reduce unexpected or unintended consequences of management.
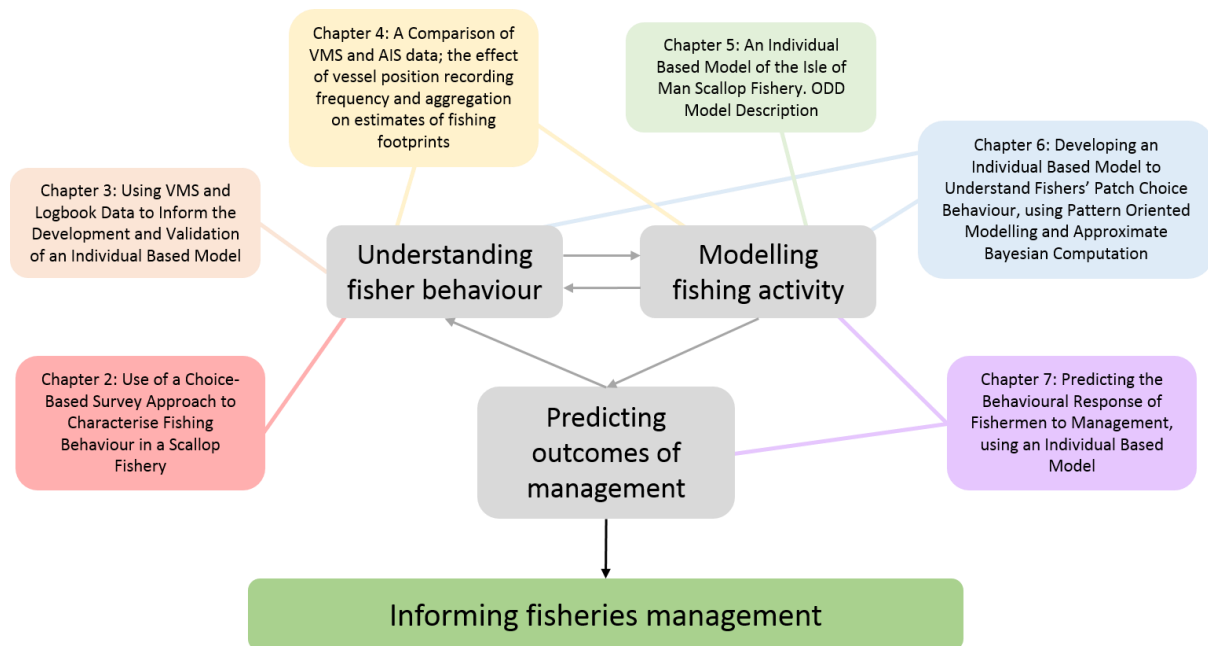

Figure 8.1. Flowchart demonstrating how each research chapter (2-7) relates to the three main themes of the thesis.

8.1. Synthesis of Research Chapters

The overall aim of the thesis was to develop a model capable of predicting fishing activity in the Isle of Man scallop fishery, to demonstrate the potential impacts of different management scenarios. The research demonstrated the utility of individual-based modelling for understanding and predicting fishing activity, and for simulating the likely impacts of management, and presented insights into fishing behaviour that could be relevant to modelling fishing activity in a wide range of fisheries. Here, a synthesis is presented, discussing how throughout the model development, each chapter has contributed to scientific research in each of the three main themes: understanding fisher behaviour, modelling fishing activity, and predicting the outcome of management.

8.2. Understanding Fisher Behaviour

8.2.1. Economic Rationality

A theme carried through several chapters was that fishers may not always aim to maximise their profits, and may not always behave in an economically rational way that would conform to optimal foraging theory (Abernethy *et al.*, 2007; Christensen and Raakjær, 2006; Holland, 2008; Salas and Gaertner, 2004). The questionnaire data and conjoint analysis suggested that some fishers had the potential to achieve higher catches (Chapter 2); the fishing grounds that were most prosecuted were not necessarily the grounds at which fishers achieved the highest catches (Chapter 3); and modelling fishers as optimal foragers, selecting patches with the highest expected catch, overestimated catches (Chapter 6). The presence of satisficing behaviour (Christensen and Raakjær, 2006; Jager *et al.*, 2000; Salas and Gaertner, 2004) was also demonstrated, where fishers aim for a certain level of catch or income, rather than fishing for the maximum time or effort permitted to maximise their catch. During the questionnaires, fishers provided threshold values for catches they considered 'good' or a 'minimum viable' catch, which were demonstrated as realistic when compared to logbook records (Chapter 2). Modelling fishers as returning to port after they had achieved one of these threshold catches better reproduced the changes in fishing activity following area closures, than modelling them as fishing until curfew or until they had reached the maximum time they would be willing to fish for (Chapter 7). Informal discussions during interviews suggested that for some fishers this could be related to reasons as simple as wanting to make a living doing something they enjoy rather than being in it for the money; aiming to maintain a better balance between fishing and family life; or being closer to retirement and therefore perhaps more risk averse. In short, fishers may strive for a healthy work-life balance and value aspects of job satisfaction differently, just as in

other professions (Pollnac and Poggie, 2008; Seara *et al.*, 2017). Modelling all fishers as economically rational individuals who successfully strive for the maximum possible catch may therefore overestimate both catches and the ability of economic incentives to alter the behaviour of fishers to achieve a policy goal (Holland, 2008; Smith and Wilen, 2005).

Pollnac and Poggie (2008) suggested that fishing attracts a certain personality, and that the active and adventurous aspects of fishing are also highly attractive alongside financial returns; fishing makes fishermen happy. Whilst running a fishing vessel is a business, not all fishers may be as economically driven or ambitious as others, and may make decisions in different ways (Chapter 2 & 3). Following some relatively strict management controls in the queen scallop fishery in 2014, including bag limits and area closures, some fishers stated that catches were severely reduced, and were unhappy, but others suggested that they could still make a living, were happy to work a short day (because the daily bag limits could be met sooner than the curfew), and they received a better price for the catch as the lower availability drove higher market values. In addition, instead of moving to the opposite side of the island, where higher catch rates could be achieved, some vessels were either unwilling or unable to change location, and remained fishing over seemingly unprofitable grounds (Karen McHarg, DEFA, pers. comms.). To understand the response of fishers to management, and to provide appropriate incentives to change behaviour, it would likely be beneficial to give more consideration to the driving motivations and different perspectives of fishers (Gelcich *et al.*, 2005).

8.2.2. Behavioural complexity

Fisheries are complex systems; it may be difficult to distil fishing behaviour down into simple, generalised rules. Whilst fishers, of course, try to fish where they are likely to achieve good catches, there are numerous other factors and variables that can influence the decision of where to fish (Abernethy *et al.*, 2007; Christensen and Raakjær, 2006; Holland, 2008). The sea state and distance to port were demonstrated as important to fishers in deciding where to fish, as were the meat yield, roe status, and rock content (i.e. habitat complexity) (Chapter 2). However, habit and personal preference also appeared to play an important role too, which are more difficult to quantify (Chapter 3). During the questionnaire interviews, some fishers provided a high level of detail about how they decide where to fish, including slight differences in their substrate preference when the dredge teeth are worn to different extents, the direction in which they would tow in different tides, and referring to specific physical structures on the seabed. Whilst these may all contribute to a fisher's decision of where to fish, attempting to include everything that influences the decision

process would likely yield an overly complex model. There is a need to identify the most important, and most quantifiable variables, which can be included in a model design.

Throughout the model development and validation it became apparent that incorporating a random element of fisher behaviour was important to reproducing realistic patterns of fishing activity (Chapter 6). This does not mean that fishers decide where to fish at random, but rather suggests that a random component to the model design may account for additional variables not explicitly accounted for in the processes in the model. The importance of this random element may increase as the season progresses, as the distribution of scallops becomes less clustered, and it is more difficult for fishers to accurately target the areas of higher densities (Murray *et al.*, 2011). In addition, in a model setting it could be difficult to quantify the influence of gut feeling, habit, and heuristics when deciding where to fish (van Putten *et al.*, 2012); a random component may have accounted for some of this behaviour.

8.2.3. Heterogeneity

There was considerable spatial, temporal, and individual heterogeneity in fishing activity (Chapter 2 & 3). The power and capacity of vessels differed (Chapter 3), their tolerance to environmental conditions differed (Chapter 2), and their catches differed (Chapter 3). In addition, there was spatial variation in catches, for example, the most prosecuted grounds were not the grounds which yielded the highest catches, and fishers showed individual preferences for small areas of the available grounds (Chapter 3). The likelihood of fishing each day also varied between fishers. As the sea state increased, the likelihood of fishing decreased, and fishers were less likely to fish as the season progressed and catches reduced. However, there was variation in the response of each fisher (Chapter 3). Fishers responses to management can depend on attitudes, personalities and livelihoods, and so can vary between individuals (Gelcich *et al.*, 2005). To more fully understand the response of, and impact on, individual fishers in a fishery, it may be necessary to include individual variation in the model design.

Individuals in an IBM can have varying characteristics, requirements, and behaviours, which can influence their interaction with the model environment (Grimm and Railsback, 2005, Chapter 5). Nevertheless, the level of heterogeneity that should be accounted for and validated within a model depends on the problem to be modelled. Increased model complexity can make validation, communication, and application more difficult (Cartwright *et al.*, 2016), therefore unnecessary complexity should be omitted from a model design. Iterative model development cycles should

begin as deliberately oversimplified, and evolve according to discrepancies between model outputs and real data to ensure that only necessary complexity is included (Grimm *et al.*, 2014; Grimm and Railsback, 2005). This thesis aimed to develop a simple model, using simple behavioural rules derived from theory, and bound by realistic limits ascertained from questionnaires, to ensure that behaviours were realistic (Chapter 2 & 5). Using these simple rules, the model was able to recreate patterns in fishing activity with reasonable accuracy (Chapter 6).

8.3. Modelling Fishing Activity

8.3.1. Model Validation

This thesis has demonstrated the use of Pattern Oriented Modelling (POM) and Approximate Bayesian Computation (ABC) in determining the most realistic model structure to predict fishing activity in the Isle of Man scallop fishery (Grimm *et al.*, 2005; Grimm and Railsback, 2012; van der Vaart *et al.*, 2015). There were two stages to model validation: model output verification (Chapter 6) and model output corroboration (Chapter 7). In model output verification the model was 'tweaked' to increase its ability to reproduce patterns seen in data used to develop the model, through model selection and through adding a random component to behaviour (Chapter 6). It is more straightforward for a model to recreate patterns seen in the fishery during model output verification because the data was used during model development, and the model is altered to specifically improve its ability to reproduce this data (Augusiak *et al.*, 2014; Grimm *et al.*, 2014). In Chapter 6, models that did not have an element of random behaviour were selected against, as were models in which fishers selected fishing patches with the highest expected catch rates. The most accepted patch choice decision model was to decide where to fish based on the utility of a patch, derived from the conjoint analysis (Chapter 2 & 6). Incorporating a random element of fishing behaviour appeared to be important to capture the processes not explicitly accounted for in the model structure (e.g. gut feeling, habit, heuristics, or just an inability to target the areas with highest catches).

In the model output corroboration, the model output was compared to independent data not used during model development (Augusiak *et al.*, 2014; Grimm *et al.*, 2014). Recreating these patterns can provide more weight to the body of evidence supporting a models credibility, because the model has not been calibrated to recreate these patterns. In particular, if there are new patterns against which a model can be tested, that were un-used or unknown during model development, this can provide strong evidence that a model is structurally realistic (Grimm *et al.*, 2014). In Chapter 7, the model was used to simulate fishing activity following new area closures; these closures did not form part of

the dataset used during model output verification. The model was able to recreate some realistic values and trends, but average trip landings, and the overall total landings, were underestimated. The behaviours which best recreated the absolute values in the fishery data were not the behaviours which best reproduced the trends in values. Further model development may improve the model fit, so that both the correct trend, and magnitude, are reproduced.

ABC provided a quantitative and objective method of model validation (van der Vaart *et al.*, 2015). In this thesis, parameters provided by fishers were assumed to be realistic (Chapter 2), therefore model selection was performed without calibration. ABC provided an objective way to determine which model structures best reproduced the patterns and values seen in the real fishery. Fishery IBMs are often presented with little consideration given to alternative behavioural submodels (Bastardie *et al.*, 2014; Little *et al.*, 2009); here ABC has been demonstrated as a relatively straightforward method to contrast different model structures during the model selection process, increasing model transparency (Chapter 6).

8.3.2. Model Uncertainty

Contrasting alternative behavioural submodels provided insights into fisher behaviour, and identified which behaviours produced the most realistic model (Chapter 6). Throughout the model validation process it was not possible to identify a single 'best' overall model structure; there were a range of 'patch choice decision', 'between patch decision', and 'return to port decision' submodels present in the best performing models. Model selection does not imply that there is one correct model (Ripley, 2004), as different mechanisms in a model could lead to the same emergent patterns (Csillery *et al.*, 2010), but it identifies a range of plausible model structures. Retaining a range of model structures to use in simulation experiments may allow uncertainty in model predictions to be better understood, and the range of likely outcomes of management to be explored (Chapter 7). The model predicted different impacts from a range of hypothetical area closures; some were likely to cause a decrease in catches, some had little impact on catches, and some may lead to an increase in catches. There was, however, considerable variation in the model predictions within a closed area scenario; depending on what model structure was used to make the prediction, the impacts of the management varied (Chapter 7).

Models are an important tool for fisheries scientists, as *in situ* experiments to see how fisheries would respond to novel management scenarios are neither feasible nor ethical, but their use must be guided by an understanding of the assumptions, limitations, and uncertainty associated with

them (Cartwright *et al.*, 2016). The model presented here could aid decision-makers in exploring the potential outcomes of management, but the uncertainty surrounding predictions was relatively high (Chapter 7). It is important that this uncertainty can be successfully communicated to managers and stakeholders, to prevent inappropriate application of the model, or over-confidence in model predictions (Cartwright *et al.*, 2016). Using a standardised protocol to describe the model and documenting model output verification and model output corroboration increases model transparency (Chapter 5, 6 & 7; Grimm *et al.*, 2006, 2010, 2014; Augusiak *et al.*, 2014). In addition, reporting the stages of model development, documenting the assumptions made, submodels tested, and model selection process, can provide the evidence needed by decision-makers to make an informed decision of how to use a model (Augusiak *et al.*, 2014; Grimm *et al.*, 2014).

8.4. Predicting the Outcome of Management

The aim of this thesis was to develop a simulation tool that could potentially be used by both fishers and managers to explore the outcome of different management scenarios. To demonstrate the use of the tool, the likely outcomes of a series of hypothetical closed area scenarios were simulated. They demonstrated that the spatial arrangement of closed areas could substantially influence the outcome of management, in terms of the change in fishing footprint, catches, and fuel costs (Chapter 7). Protecting the same amount of scallop stock biomass could be achieved in several different ways, which had different impacts on the resulting fishing footprint, catches, and fuel costs. Protecting larger areas of low density scallops could be the most favourable course of action, as it caused the greatest reduction in fishing footprint, whilst predicting a possible increase in catches through fishers being directed to the higher density fishing grounds (Chapter 7). Nevertheless, fishers have been demonstrated to view the stated benefits of area closures with scepticism, just as advocates of area closures have been demonstrated to view fishers' assertions about economic costs with scepticism (Smith *et al.*, 2010). The capacity for both fishers and decision-makers to test out different management options in this way before implementation could allow more informed decisions, and better compromises between management objectives.

During the questionnaire interview completed in Chapter 2, fishers were asked what was the most unpredictable part of the fishery. Whilst 69% responded 'the weather', 31% responded 'the government'; a third of fishers felt that the management decisions made by the government were as unpredictable as the weather. The model developed during this PhD could be a first step towards a simulation tool that could facilitate discussion between fishers and managers about the different management options and the likely outcomes. Model outputs were displayed in simple, intuitive

plots, colour coded according to the potential impacts to fishers and the environment, in terms of the projected change in fishing footprint, scallop catches, and fuel costs (Figure 8.2a). In addition, through displaying the range of outcomes from individual model simulations, the uncertainty surrounding a scenario could be visualised. Figure 8.2b displays example output from three illustrative scenarios. The predicted outcome of the turquoise scenario was more certain, visualised by a tighter clustering of model outputs. Whilst the overall uncertainty of the blue and pink scenarios is similar, a higher proportion of the pink model outputs lie in the green quadrant of the figure, suggesting it is more likely to have a positive impact on the fishery than the blue scenario. It does, however, also illustrate how one pink model output predicted a negative impact on the fishery both in terms of the fishing footprint and catches (Figure 8.2b). It is important to be able to effectively communicate the uncertainty in model predictions to both decision makers and stakeholders (Cartwright *et al.*, 2016); using intuitive figures such as these could help facilitate understanding of the likely outcomes predicted by the model, and the uncertainty surrounding these predictions.

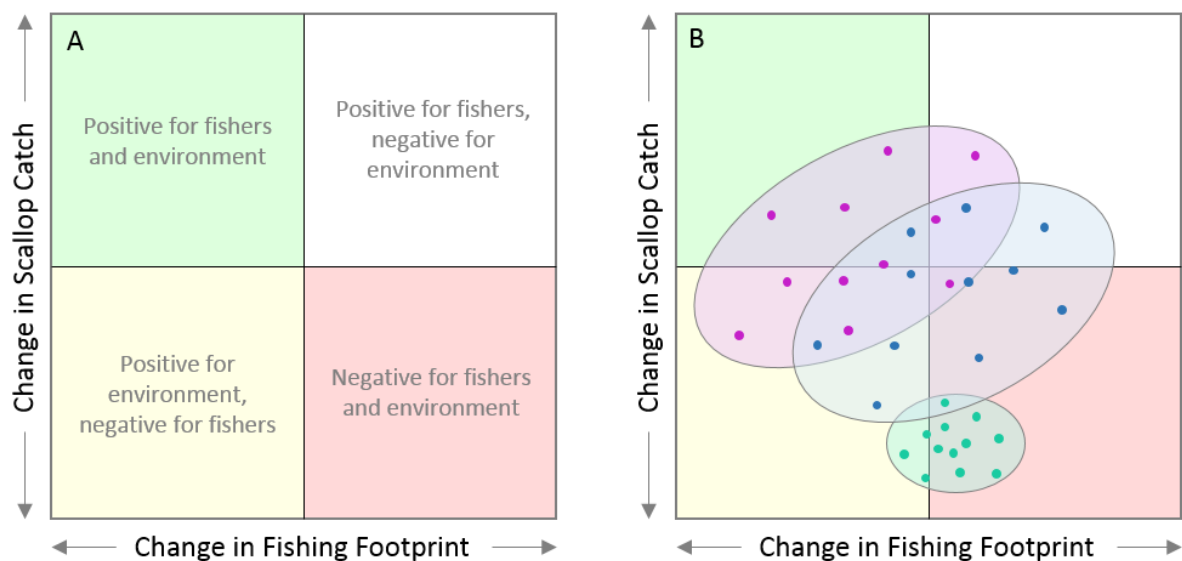*Figure 8.2. Example outputs from management simulations, coloured coded to display whether the model predicted a positive or negative impact to the fishery. The clustering of points illustrates the level of uncertainty in the predictions made for a particular scenario, and the position of the points indicates the likely impacts. The variables on each axis could be varied according to the management objectives.*

8.5. Evaluation of the Approach

8.5.1. Individual-based Modelling

This thesis has demonstrated the utility of IBMs for both understanding fisher behaviour, and for predicting likely outcomes of management. There is a perception that IBMs are data heavy, but this thesis has shown that minimal data collection is required in a fishery with existing vessel tracking data. Two fundamental pieces of information required to predict the environmental impacts of a fishery are information on the distribution of stocks, and information on the distribution of activity (Kaiser *et al.*, 2016). Hence, these pieces of information are often already available to fisheries scientists. Beyond these, this work has demonstrated that the only additional data required to develop an IBM of a fishery can be collected through interviews and questionnaire surveys. There is increasing interest in applying individual-based modelling to fisheries (Burgess *et al.*, 2017), and an increasing call to include fishermen in the modelling and evaluation of management strategies (Mackinson and Wilson, 2014; Voinov and Bousquet, 2010; www.gap2.eu); Cartwright *et al.,* (2016) have also demonstrated how individual-based modelling can be a good tool for participatory modelling and co-management. Advances in computing power and technology have also made it more cost and time effective to build simulation models and run comprehensive validation analyses (van der Vaart *et al.*, 2015). In particular, using Approximate Bayesian Computation it was possible to relatively easily compare and contrast multiple behavioural submodels and model structures, which constituted an important step in working towards a robust, structurally realistic model (Chapter 6). This PhD has demonstrated how a fishery IBM can be built using often already available data, supplemented by questionnaire data, to provide realistic predictions of fishing activity, and provide valuable insights into fishing behaviour. Further development of this model could improve our ability to predict how fishermen would respond to management, reducing unexpected outcomes.

The individual-based modelling software, NetLogo, provided a good platform on which to develop the model, with a simple but powerful programming language, a built in graphical user interface, and comprehensive documentation (Railsback *et al.*, 2006). The simple user interface was useful for troubleshooting during model development, and provided an intuitive front end to the model when discussing it with collaborators and stakeholders (Cartwright *et al.*, 2016). In addition, a simple interactive feature allows users to draw closed area scenarios in the model user interface, and instantly run a model simulation with them, but also export them to a .csv file for formal analysis. Nevertheless, NetLogo was originally developed as a teaching tool, and thus the ability to run simulation experiments and statistically analyse the outputs within it is limited (Thiele *et al.*, 2012). The development of an R package, *RNetLogo*, means that NetLogo models can be controlled and run

from R, and model results easily transferred back to R to statistically analyse the results (Thiele *et al.*, 2012). Using *RNetLogo* it is possible to automate a series of simulation experiments, leading to more rigorous model analyses and validation, and allowing the better use of IBMs to answer theoretical and applied questions (Thiele *et al.*, 2012). In this thesis, the use of *RNetLogo* substantially increased the scope for running model simulations, allowing a more comprehensive model development and validation phase than if running simulations through the built-in NetLogo simulation experiment feature. In addition, programming the model simulations through R meant the model could easily be run on the supercomputer at HPCWales, which would not have been feasible through NetLogo itself.

8.5.2. Data Sources

There can be scepticism amongst some scientists about the value of fisher knowledge, and whether this type of data are accurate; throughout this thesis we have provided further evidence that data collected directly from fishers can be reliable, accurate, and valuable (Bundy and Davis, 2013; O'Donnell *et al.*, 2012; Shepperson *et al.*, 2014, 2016; Teixeira *et al.*, 2013). During the questionnaire interviews fishers provided information on vessel characteristics, environmental and physical limitations to their activity, and basic economic information. Where possible, these data were verified against VMS and logbook data, which showed a good level of accuracy (Chapter 2). An obvious concern is that fishers may bias the data they provide, to minimise restrictions to them. However, it would be difficult to quickly compute how to skew the answers to an agenda considering that the parameters were to be put into a model of behaviour. It would be even more difficult to bias the answers in the conjoint analysis, as respondents simply selected between virtual fishing patches of varying environmental conditions (Chapter 2). Further, no calibration of the parameters derived from the questionnaire interviews was required to reasonably well reproduce patterns in fishing activity (Chapter 6), which provides further confidence that the data was reliable and accurate. This thesis has therefore contributed to the growing body of evidence that fishers can provide valuable information, increasingly demonstrated to be a reliable source (Bundy and Davis, 2013; O'Donnell *et al.*, 2012; Shepperson *et al.*, 2014; Teixeira *et al.*, 2013).

Questionnaire interviews provided both quantitative parameters and contextual information to help understand fishing activity, whilst VMS and logbook data provided further information for model development, and the patterns in activity against which the model could be validated. In areas where no VMS and logbook data are available it may be possible to rely more on interview data and parameters collected directly from fishers. Automatic identification system (AIS) data is also increasingly recognised as a potential alternative to VMS as a source of spatial data on fishing

activity (Mccauley *et al.*, 2016; Natale *et al.*, 2015; Russo *et al.*, 2016). AIS data could provide an alternative to VMS data, to develop and validate a model, in areas for which VMS data is unavailable. However, a comparison of VMS and AIS data in this thesis demonstrated substantial missing AIS data (Chapter 4). For each individual fisher, 45 – 99% of their VMS data did not have any corresponding AIS data. There may be some gaps in satellite coverage, but the variation between individuals also suggests some vessels may turn down their AIS transmitter to reduce the chance of a signal being received (Mccauley *et al.*, 2016). In addition, AIS is generally used on larger boats, greater than 24m in length, whereas as VMS is generally on vessels over 12m in length (in the EU) (EC, 2009). AIS data may therefore be more applicable if extending the model to a larger fishery, but caution would be required, considering the substantial gaps in coverage demonstrated here.

8.6.   Limitations and Future Work

A common pitfall of IBM design is setting the scope too large or complex (Grimm and Railsback, 2005). The final model presented here represents a substantial simplification of the fishery, in terms of the behaviours included, and the level at which the model has been validated. In general a simpler model is preferable (Grimm *et al.*, 2005; Plagányi *et al.*, 2014), therefore the model was designed to be simple, and in future modelling cycles additional complexity could be incorporated as required. There are several areas in which the model may benefit from the consideration of further complexity. The model validation suggested that the return to port decision could be quite important in predicting fishing activity, specifically the total catches. This thesis focussed more on the initial patch choice decision, regarding the spatial distribution of activity; the model was better able to reproduce the extent of fishing than the total catches (Chapter 6 & 7). In the current model design, the return to port decision constituted a simple binary 'if a condition is met, return to port' rule, where the condition could be a threshold catch or time limit. Future model development could include refining this decision process so that the probability of returning to port increases as both the catch and time spent at sea increases. External vessels were not modelled as a mechanistic part of the model, due to a lack of data detailing their behaviour, rather the depletion by external vessels was simulated according to patterns in previous exploitation (Chapter 5). Future work could include extending the behaviour of the external vessels, to predict, with more detail, when and where they would likely fish. In Chapter 2 and 3 the wave height was demonstrated to be an important variable in influencing the decision of when and where to fish. In the model, sea state was accounted for in the likelihood that a vessel fished or not each day, which differed between ports, but the influence of sea state was not included when vessels decided where to fish within a trip. The predicted spatial

distribution of activity may be improved by accounting for varying sea states with a day, as on some days areas further out to sea may be prohibitively rough, whilst it may still be possible to fish in more sheltered inshore areas. The spatial distribution of fishing activity was validated at two relatively coarse scales; the total extent, and the proportion of effort over the four main grounds. The grounds were identified by splitting the 12nm Sea into four areas that encompassed each of the main grounds. However, it would be possible to validate the spatial distribution of effort at a finer scale, by identifying a finer scale set of approximate fishing grounds (Figure 8.3) (Kaiser *et al.*, 2008). Finally, all fishers followed the same behavioural rules throughout a simulation (i.e. either all vessels selected a fishing patch with above average catch rate, or all vessels selected a patch with the highest expected catch rate, etc.); a more structurally realistic model may be achieved if individual heterogeneity in behaviour was accounted for, in addition to parameterising vessels with different characteristics.
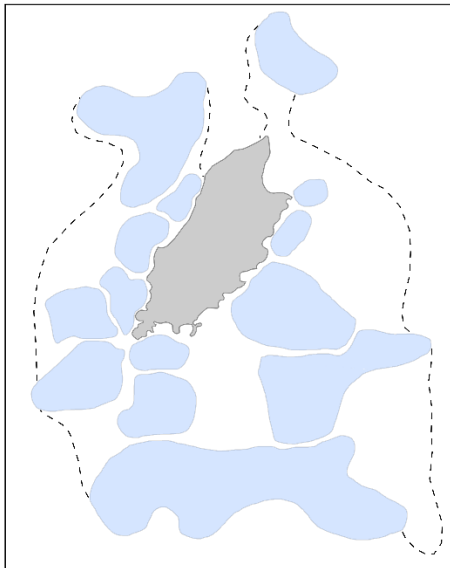

Figure 8.3. Approximate boundary lines of scallop fishing grounds in the Isle of Man, as defined in Kaiser et al, (2008). Blue patches indicate the approximate boundaries of the fishing grounds, dashed lines indicate areas where scallops occur, but are only occasionally fished. Figure digitised from Kaiser et al. (2008).

Stillman *et al.* (2015) described three stages of individual-based modelling: conceptualisation, which identifies the questions to be modelled; implementation, which includes the development and validation of a model for a typically simple initial system; and diversification, in which the model is applied to a wider range of systems or research questions, which likely involves further development and validation. The Isle of Man scallop fishery presented a data rich, simple fishery system with which to develop and validate an IBM. The stationary resource, relatively simple behavioural

structure of the system (e.g. single day trips), and comprehensive data coverage made it an ideal system to develop a simple model, to understand more about predicting fisher behaviour and how such a model could be designed, validated, and applied in management (Stillman *et al.*, 2015). The model was designed in a generalised way, and so could be parameterised for other similar fisheries relatively easily during a diversification phase (e.g. Isle of Man queen scallop fishery and the English Channel inshore scallop fishery, as well as other relatively immobile species such as crab and lobsters). The model focused on the short term decisions made by fishers, i.e. decisions about how current fishing capacity was used, such as temporal and spatial effort allocation, area restrictions, and seasonal regulations (Hatcher *et al.*, 2000; van Putten *et al.*, 2012). It did not simulate long term decisions that affected the level of fishing capacity, such as entry exit decisions (van Putten *et al.*, 2012), which limits the models longer term predictive capability. As the model was designed to only run over one fishing season, and the total stock biomass was estimated, it was reasonable to have a simplified stock status with no recruitment. Extending the model to other fisheries, and for longer term predictions, may require a more complex stock model, and explicitly predicted levels of effort. Interactions with other fisheries (e.g. conflict between towed and static gear) and with other sectors (e.g. renewable energy development) could also be explored.

Despite the simplifying assumptions, the model was able to reproduce patterns in the Isle of Man scallop fishery with reasonable accuracy. The outputs from this IBM could be linked with a tool currently in development for the Marine Stewardship Council, which predicts the impact on, and recovery of, habitats following a defined fishing impact. Combining two tools to predict the redistribution of fishing effort following an area closure, including the impacts on the stock, the fishers' income, and the wider environmental impacts of a changing footprint, could provide a comprehensive evaluation of management scenarios, leading to more informed management.

8.7. Final Conclusions

This thesis has demonstrated the potential for using individual-based modelling to better understand fishing behaviour and to predict the likely outcomes of management. In particular, it has highlighted the importance of contrasting different submodels of fishing behaviour, to determine the most realistic model structure. It illustrated the importance of incorporating random behaviour in a model design, potentially to account for more difficult to quantify, social aspects of fishing decisions, not related to expected catches. This thesis has also provided strong evidence to support the use of questionnaire interview data in modelling fishing activity. Questionnaire responses were demonstrated to be accurate when directly compared with VMS and logbook data, and when used

to parameterise the model they required no calibration to recreate fishing activity with reasonable accuracy. The work presented here represents a first step towards a simulation tool that could be used by both fishers and managers to evaluate the potential impacts of management scenarios, reducing the likelihood of unexpected or unintended consequences of management.

8.8. References

Abernethy, K. E., Allison, E. H., Molloy, P. P., and Côté, I. M. 2007. Why do fishers fish where they fish ? Using the ideal free distribution to understand the behaviour of artisanal reef fishers. Canadian Journal of Fisheries and Aquatic Sciences, 64: 1595–1604.

Augusiak, J., Van den Brink, P. J., and Grimm, V. 2014. Merging validation and evaluation of ecological models to 'evaludation': A review of terminology and a practical approach. Ecological Modelling, 280: 117–128.

Bastardie, F., Nielsen, J. R., and Miethe, T. 2014. DISPLACE: a dynamic, individual-based model for spatial fishing planning and effort displacement — integrating underlying fish population models. Canadian Journal of Fisheries and Aquatic Sciences, 71: 1–21.

Bundy, A., and Davis, A. 2013. Knowing in context: An exploration of the interface of marine harvesters' local ecological knowledge with ecosystem approaches to management. Marine Policy, 38: 277–286.

Burgess, M., Drexler, M., Axtell, R., Bailey, R., Watson, J., Ananthanaryanan, A., Cabral, R., *et al.* 2017. The role of agent-based modeling in systems-based fishery management. Fish and Fisheries (In Review).

Cartwright, S. J., Bowgen, K. M., Collop, C., Hyder, K., Nabe-Nielsen, J., Stafford, R., Stillman, R. A., *et al.* 2016. Communicating complex ecological models to non-scientist end users. Ecological Modelling, 338: 51–59.

Christensen, A.-S., and Raakjær, J. 2006. Fishermen's tactical and strategic decisions. A case study of Danish demersal fisheries. Fisheries Research, 81: 258–267.

Csillery, K., Blum, M. G. ., Gaggiotti, O. E., and Francois, O. 2010. Approximate Bayesian Computation (ABC) in practice. Trends in Ecology & Evolution, 25: 410–418.

EC. 2009. Council Regulation (EC) No. 1224/ 2009 of 20 November 2009 Establishing a Community control system for ensuring compliance with the rules of the Common Fisheries Policy. Official Journal of the European Union, L343/1: 1–50.

Fulton, E. a, Smith, A. D. M., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Gelcich, S., Edwards-jones, G., and Kaiser, M. J. 2005. Importance of Attitudinal Differences among Artisanal Fishers toward Co-Management and Conservation of Marine Resources, 19: 865–875.

Grimm, V., Augusiak, J., Focks, A., Frank, B. M., Gabsi, F., Johnston, A. S. A., Liu, C., *et al.* 2014. Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. Ecological Modelling, 280: 129–139.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., *et al.* 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 198: 115–126.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., and Railsback, S. F. 2010. The ODD protocol: A review and first update. Ecological Modelling, 221: 2760–2768.

Grimm, V., and Railsback, S. F. 2005. Individual-Based Modeling and Ecology. Princeton University Press, Princeton.

Grimm, V., and Railsback, S. F. 2012. Pattern-oriented modelling: a 'multi-scope' for predictive systems ecology. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 298–310.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H. H., *et al.* 2005. Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. Science, 310: 987-991.

Hatcher, A., Jaffry, S., Thebaud, O., and Bennett, E. 2000. Normative and Social Influences Affecting Compliance with Fishery Regulations. Land Economics, 76: 448–461.

Hilborn, R. 2007. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Holland, D. 2008. Are Fishermen Rational? A Fishing Expedition. Marine Resource Economics, 23: 325–344.

Jager, W., Janssen, M. A., De Vries, H. J. M., De Greef, J., and Vlek, C. A. J. 2000. Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model. Ecological Economics, 35: 357–379.

Kaiser, M. J., Hilborn, R., Jennings, S., Amaroso, R., Andersen, M., Balliet, K., Barratt, E., *et al.* 2016. Prioritization of knowledge-needs to achieve best practices for bottom trawling in relation to seabed habitats. Fish and Fisheries, 17: 637–663.

Kaiser, M. J., Murray, L., Hinz, H., and Mclay, A. 2008. Isle of Man sustainable fisheries strategy. Fisheries & Conservation report No. 1, Bangor University. 11 pp.

Little, L. R., Punt, A. E., Mapstone, B. D., Begg, G. a., Goldman, B., and Williams, A. J. 2009. An agent-based model for simulating trading of multi-species fisheries quota. Ecological Modelling, 220: 3404–3412.

Mackinson, S., and Wilson, D. C. K. 2014. Building bridges among scientists and fishermen with participatory action research. *In* Social Issues in Sustainable Fisheries Management MARE Publication Series Volume 9, pp. 121–139.

Mccauley, B. D. J., Woods, P., Sullivan, B., Bergman, B., Jablonicky, C., Roan, A., Hirshfi, M., *et al.* 2016. Ending hide and seek at sea. Science, 351: 1148–1150.

Murray, L., Hinz, H., and Kaiser, M. 2011. Functional response of fishers in the Isle of Man scallop fishery. Marine Ecology Progress Series, 430: 157–169.

Natale, F., Gibin, M., Alessandrini, A., Vespe, M., and Paulrud, A. 2015. Mapping fishing effort through AIS data. PLoS ONE, 10: 1–16.

O'Donnell, K. P., Molloy, P. P., and Vincent, A. C. 2012. Comparing Fisher Interviews, Logbooks, and Catch Landings Estimates of Extraction Rates in a Small-Scale Fishery. Coastal Management, 40: 594–611.

Plagányi, É. E., Punt, A. E., Hillary, R., Morello, E. B., Thébaud, O., Hutton, T., Pillans, R. D., *et al.* 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries, 15: 1–22.

Pollnac, R. B., and Poggie, J. J. 2008. Happiness, well-being and psychocultural adaptation to the stresses associated with marine fishing. Human Ecology Review, 15: 194–200.

Railsback, S. F., Lytinen, S. L., and Jackson, S. K. 2006. Agent-based Simulation Platforms: Review and Development Recommendations. SIMULATION, 82: 609–623. SAGE Publications.

Ripley, B. D. 2004. Selecting amongst large classes of models. *In* Methods and Models in Statistics: In Honour of Professor John Nelder, FRS, pp. 155–170. Ed. by N. Adams and E. Al. Imperial College Press.

Russo, T., D'Andrea, L., Parisi, A., Martinelli, M., Belardinelli, A., Boccoli, F., Cignini, I., *et al.* 2016. Assessing the fishing footprint using data integrated from different tracking devices: Issues and opportunities. Ecological Indicators, 69: 818–827.

Salas, S., and Gaertner, D. 2004. The behavioural dynamics of fishers: management implications. Fish and Fisheries, 5: 153–167.

Seara, T., Pollnac, R. B., Poggie, J. J., Garcia-Quijano, C., Monnereau, I., and Ruiz, V. 2017. Fishing as therapy: Impacts on job satisfaction and implications for fishery management. Ocean & Coastal Management, 141: 1–9.

Shepperson, J., Murray, L. G., Cook, S., Whiteley, H., and Kaiser, M. J. 2014. Methodological considerations when using local knowledge to infer spatial patterns of resource exploitation in an Irish Sea fishery. Biological Conservation, 180: 214–223.

Shepperson, J., Murray, L. G., Mackinson, S., Bell, E., and Kaiser, M. J. 2016. Use of a choice-based survey approach to characterise fishing behaviour in a scallop fishery. Environmental Modelling & Software, 86: 116–130.

Smith, M. D., Lynham, J., Sanchirico, J. N., and Wilson, J. A. 2010. Political economy of marine reserves: Understanding the role of opportunity costs. Proceedings of the National Academy of Sciences, 107: 18300–18305.

Smith, M. D., and Wilen, J. E. 2005. Heterogeneous and Correlated Risk Preferences in Commercial Fishermen: The Perfect Storm Dilemma. Journal of Risk and Uncertainty, 31: 53–71.

Stillman, R. A., Railsback, S. F., Giske, J., Berger, U., and Grimm, V. 2015. Making predictions in a changing world: The benefits of individual-based ecology. BioScience, 65: 140–150.

Teixeira, J. B., Martins, A. S., Pinheiro, H. T., Secchin, N. A., Leão de Moura, R., and Bastos, A. C. 2013. Traditional Ecological Knowledge and the mapping of benthic marine habitats. Journal of Environmental Management, 115: 241–50.

Thiele, J. C., Kurth, W., and Grimm, V. 2012. RNETLOGO: an R package for running and exploring individual-based models implemented in NETLOGO. Methods in Ecology and Evolution, 3: 480–483.

van der Vaart, E., Beaumont, M. A., Johnston, A. S. A., and Sibly, R. M. 2015. Calibration and evaluation of individual-based models using Approximate Bayesian Computation. Ecological Modelling, 312: 182–190.

van Putten, I. E., Kulmala, S., Thébaud, O., Dowling, N., Hamon, K. G., Hutton, T., and Pascoe, S. 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish and Fisheries, 13: 216–235.

Voinov, A., and Bousquet, F. 2010. Modelling with stakeholders. Environmental Modelling & Software, 25: 1268–1281.