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Predicting the impact of hook decrements on the distribution of fishing effort in the Eastern Tuna and Billfish Fishery

Final report FRDC project 2008/028

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Important Disclaimer

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Non-technical summary

2008/028	Predicting the impact of hook decrements on the distribution of fishing effort in the Eastern Tuna and Billfish Fishery

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OBJECTIVES:

1 Develop a statistical (multivariate logit) model to predict the distribution of fishing effort in the ETBF

2 Develop a process (a state-dependent behavioral) model of effort allocation for an input managed fishery with individual effort allocations

3 Evaluate the impact of a series of SAF scenarios on the distribution of fishing effort in the ETBF using statistical and state-dependent behavioral models

Outcomes Achieved to Date

The primary outcome of the project is an increased understanding of the factors driving the spatial distribution of fishing effort in the Eastern Tuna and Billfish Fishery and the effects of those factors on the economics of the fishery at the vessel, port, and fleet level. Prior to this project there had been very little analysis of fleet dynamics in the fishery, and thus no formal information on how the fleet might react to spatial management. The primary outcome of this project is to provide a resource for AFMA managers and the Resource Assessment Group and Management Advisory Committee members that can assist in understanding the outcomes of management actions. Secondarily, while the primary fishery management structure has shifted from spatial effort controls to nonspatial catch quotas, there is still a need for spatial management for specific issues such as bycatch of TEP species and target species of other fisheries. The analysis developed in this project can readily be adapted to answer questions about fleet dynamics under a catch quota system, and forms a basis for addressing questions arising from the new management structure. In terms of response to the project by industry, managers and other stakeholders, the rapid change in the management structure of the fishery has meant that engagement is difficult due to shifting priorities. However, the project team has engaged with the managers, industry and the Resource Assessment Group several times in order to increase the relevance of the models developed and raise awareness about the utility of the project for management of the fishery.

Background

The *Eastern Tuna and Billfish Fishery Management Plan 2005* introduced a system of statutory fishing rights in the form of individual transferable effort quotas based on the number of hooks employed by each vessel, and a corresponding total allowable effort level (total number of hooks that can be deployed in the fishery). In addition, a system was introduced aimed at limiting the catch of particular species (both target and bycatch) by setting different hook penalty rates from fishing in particular areas.

The effectiveness of such a system will largely be dependent on the degree to which fishers respond to changing incentives created by the policy. The spatial hook penalty effectively reduces the value per hook associated with fishing in a particular area, making other areas potentially more attractive. This will encourage fishers who are able to fish elsewhere, while those who choose to continue fishing in the affected area are still able to do so, but the total effort quota consumed will be increased (potentially resulting in overall lower levels of fishing effort).

In this study, two models were developed and used to estimate the effects of introducing hook penalties on the distribution of fishing effort in the fishery. The impact on economic performance was also considered through estimating the proportional changes in total fishery revenue and fuel costs.

The models

The first type of model is a statistical model that estimates the probability of a fisher operating in a given area based on the characteristics of the area (e.g. average revenue per unit effort, distance from port etc) and the characteristics of the fisher. The model, known as a random utility model (RUM) assumes historical effort allocation choices are based on the concept of utility maximisation, and this is based on expected revenues and costs from fishing in a given area. In the model, the allocation of effort of the individual fisher to each area is estimated as the product of the total effort expended by the fisher and the probability that effort will be applied to each area. The total spatial effort allocation is derived by summing the effort in each area of the individual fishers.

The second type of model is a dynamic programming model that determines an optimal effort allocation based on revenues, costs and the opportunity cost of using up the effort quota each trip (something ignored by the RUM). The model, known as a dynamic state variable model (DSVM) is less reliant on historical effort patterns, and is hence more responsive to changes in conditions. As with the RUM, total effort is summed over a number of simulated vessels that make their decisions based on knowledge of species distributions, expectations of catch, expectations of prices and costs of fishing.

Model analyses and key results

The models were applied to a number of scenarios involving different areas of the fishery subjected to either a full closure or different levels of hook penalty. We consider 20 scenarios i) 3 levels of hook decrement; ii) 3 locations for application of incentives and iii) 2 alternative years representing different conditions in the fishery (3 x 3 x 2 = 18); plus "baseline" scenarios of "no management" for each of the two years considered. Identical scenarios were considered for different years since fish distribution, availability and targeting practices show strong differences between years.

In both models, the introduction of a hook penalty resulted in a reduction in fishing effort in locations with increased penalties, and the magnitude of this reduction generally increased with the increasing hook penalty. The DSVM model was more sensitive than the RUM model in terms of response to the hook penalty, with greater reductions being observed in all scenarios. The DSVM model attaches a higher cost to the use of a hook at any point in time as it has an opportunity cost in terms of its foregone future use. The RUM, in comparison, is myopic as it treats all trips independently, and only considers the relative benefits of fishing in each area in one point in time.

The model estimates of change in fleet profitability varied considerably. In all simulations, however, a closure off Brisbane resulted in an increase in total fleet profitability. This was largely driven by cost savings from the more southerly vessels not travelling to these areas. In other scenarios, the RUM predicted a net reduction in profitability at the fleet level, although the DSVM suggested that profits may increase with a 3:2 hook penalty, and also with a closure.

Changes in profits at the individual port level suggest that the use of hook penalties, and indeed any spatial management, may have substantial consequences for the distribution of profits between ports.. The southern port of Ulladulla appears particularly vulnerable to any management measure imposed in the areas off Sydney or south of Sydney. Given 2004 conditions, the vessels in the port would have been economically unviable under any scenario in these areas, while vessels in Sydney would also have been economically unviable if the area off Sydney had been closed. Assuming 2007 conditions, vessels in Ulladulla would, again, be economically unviable under any of the modelled management options if applied in the area south of Sydney, and would be economically unviable if the area off Sydney was closed.

Implications for use of incentive based measures

A key result of this study is that spatial input controls – including closures – have inconsistent outcomes in fisheries with a mobile resource. Within each of the modelling approaches, overall fishery profitability shows no consistent pattern of increase or decrease with the increasing strength of the management measure. There was instead high variability in effects on profit with year, with incentive level, by port and by management area. The year, port and management area variability are likely due to the high spatial and temporal heterogeneity of the fishery, both in terms of relative fish availability and costs. The response by fishers to incentives is non-linear and complex, and, in some instances, counter-intuitive.

A key advantage of the hook decrementation system in this regard, compared with an all-or-nothing closure system, is its flexibility. Hook penalties can be fine-tuned during the season in response to unexpected spatial shifts in both the target and bycatch populations. Where exploitation rates appear higher than expected for target or bycatch species, the hook penalty can be readily adjusted to reduce the incentive to fish in these areas. Further, information is collected across the fishery as a whole enabling a greater understanding of the spatial stock dynamics to be developed. In contrast, information on relative stock abundance is not revealed in a closed area.

This project commenced when incentives were being considered in context of a system of effort controls, primarily in the form of a total allowable effort system with individual statutory fishing rights in terms of gear (hook) units. Since then, a decision has been undertaken to move the fishery to an output control management system, primarily operated through individual transferable quotas (ITQs). Through ITQs, and their associated total allowable catch (TAC), limits on take of particular species – including bycatch species if the system extends this far – are directly controlled. In contrast, the hook decrementation system is an indirect control system aimed at providing incentives to change behaviour rather than limiting catch directly.

The models developed in this project could be modified to incorporate output controls, in particular the DSVM model is suited to analyzing the effects of different quota scenarios (e.g. spatially disaggregated vs aggregated fishery quota, the use of bycatch quotas). While the RUM is less suited to ITQ fisheries than the DSVM, there are potential benefits in considering how the RUM could be included into a broader bioeconomic modelling framework. An advantage of the RUM identified in the study was that it did allow for the fact that fishers do not always operate in the best areas (although why this is the case is not easy to establish). Combining a RUM model with a bioeconomic optimisation model that incorporates a measure of opportunity cost may be a useful addition to the modelling toolbox currently being developed for the fishery.

1.0 Background

Increased understanding of the spatial structure of marine ecosystems and the factors that influence the spatial distribution of fisheries has resulted in increased interest in the use of spatial management techniques, particularly – but not exclusively – marine protected areas (MPAs) (Wilen 2004). In Australia, conservation-driven spatial management measures arising from marine bioregional planning are increasingly affecting fisheries through closure of areas to fishing. MPAs are becoming a favoured management strategy for the conservation of marine biodiversity within Australia (Manson and Die 2001). In creating MPAs, however, there is often a trade off between maximising biodiversity benefits and minimising negative economic impacts on the affected fisheries (Manson and Die 2001).

MPAs are not the only spatial management measure, and in many cases alternative approaches may provide fishery as well as conservation benefits (Pascoe *et al.* 2009a). The use of spatial approaches as fishery management tools has been a substantial part of the management in some Commonwealth fisheries such as the northern prawn fishery (NPF) and the southern and eastern shark and scalefish fishery (SESSF) for some time. These have been implemented for a variety of reasons ranging from management of environmental impacts to ensuring sustainability of harvests.

By comparison, spatial management is relatively new in the Eastern Tuna and Billfish Fishery (ETBF). Until recently, the fishery was managed through licence limitation. The *Eastern Tuna and Billfish Fishery Management Plan 2005* introduced a system of statutory fishing rights (SFRs) in the form of individual transferable effort quotas based on the number of hooks employed by each vessel, and a corresponding total allowable effort level (total number of hooks that can be deployed in the fishery). Although developed in 2005 (and amended in 2007), this management plan has only recently been fully implemented. SFRs were granted to eligible persons in August 2009, with the first season under effort management commenced on 1 November 2009 and running over a 16 month period.

Of considerable concern in the fishery is bycatch of highly vulnerable species such as turtles, sharks and seabirds, particularly albatross. The spatial pattern of effort in the fishery has a strong influence on the catches of these bycatch species. Under the ITE system, a facility has been introduced to potentially influence the distribution of effort using "hook decrements" (termed sub-area factors in the management plan), which are differential decrement rates of an operator's effort allocation depending on where they fish. As opposed to direct controls, this approach relies on an incentive based approach to drive the spatial distribution of effort, as it effectively varies the value per hook employed.

The concept of hook decrements is similar to that of the individual habitat quota (Holland and Schnier 2006). These are spatial management instruments where different effort penalties are applied to different areas based on the level of damage created by fishing in those areas. Damage need not be directly monitored but rather could be a model-based estimate that takes into account the type of gear fished and the state of the habitat in the area fished based on a virtual habitat model. Habitat quotas are tradeable, allowing vessels to adjust their fishing activities to minimise their own damage. Fishers consume their quota based on where and when they fish, with the penalty system providing incentives to either operate in areas where less damage will be incurred, or adopt fishing gear that will have a lower impact. In the proposed ETBF management system, the rate at which effort quota will be consumed depends on where and when they fish. Areas and/or seasons with the potential for high levels of bycatch of species of concern could attract a high penalty rate, whereas other areas with little bycatch might attract a much lower rate.

The effectiveness of such a system will largely be dependent on the degree to which fishers respond to changing incentives created by the policy. The spatial hook penalty effectively reduces the value per hook associated with fishing in a particular area, making other areas potentially more attractive. This will encourage fishers who are able to fish elsewhere to do so, while those who chose to continue fishing in the affected area are still able, but with their total effort quota consumed at an increased rate (potentially resulting in overall lower levels of fishing effort). Of key importance to managers will be the level of incentive required to achieve a given objective, the likely locations to which that displaced effort will shift, and the expected effect on fishery economics at a variety of levels from vessel profits to economic activity in a port to fishery revenue as a whole.

In this study, two models are developed and used to estimate the effects of introducing hook penalties on the distribution of fishing effort in the fishery. The impact on economic performance is also considered through estimating the proportional changes in total fishery revenue and fuel costs. The models explored here can readily be adapted to provide similar predictions of distribution and economic impact given future management scenarios.

1.1. The Eastern Tuna and Billfish Fishery

The Eastern Tuna and Billfish Fishery (ETBF) is a tropical tuna and billfish fishery targeting fish in the boundary current off the east of Australia from the tip of Cape York to the South Australia-Victoria border (Figure 1.1). The principal target species are yellowfin tuna (*Thunnus albacares*), albacore tuna (*Thunnus alalunga*), broadbill swordfish (*Xiphias gladius*), bigeye tuna (*Thunnus obesus*) and striped marlin (*Tetrapturus audax*) with the total catch of these five species averaging around 6,500 tonnes over the period 2005-06 to 2007-08, with an average total value of around $32m (Evans 2007; ABARE 2009a).

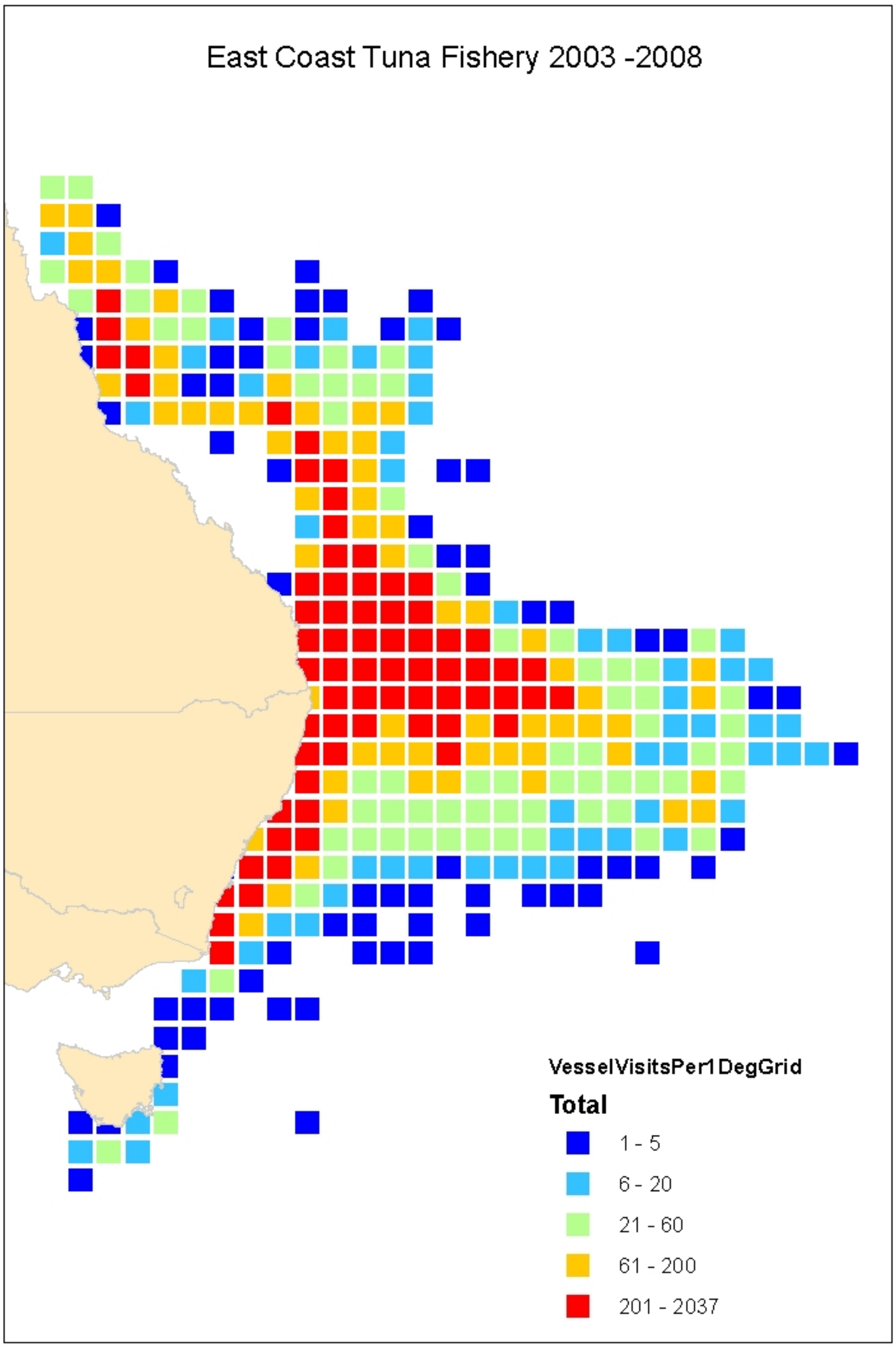

Figure 1.1 Distribution of total fishing days, 2003-08

Fishing effort is expended disproportionally over the range of the fishery (Figure 1.1), suggesting both heterogeneity in the characteristics of fishing locations, and fishers responding to this heterogeneity in their location choice. Most fishing effort is expended inshore in the southern and northern extremes of the fishery, although fishing effort extends offshore in the central part of the fishery. The fleet is relatively homogeneous across the fishery (Table 1.1) in terms of average vessel size and engine power, although within each region there is a mix of smaller and larger vessels. The smaller vessels are more limited in their range, tending to predominantly fish inshore.

The largest single port is Mooloolaba (Table 1.1), located on the Sunshine Coast north of Brisbane, accounting for nearly half of all trips in the fishery and having the largest vessels on average. While a greater number of vessels are based in southern NSW, many of these also participate in the southern bluefin tuna fishery, so their activity in the fishery is lower than their vessel numbers may imply.

Table 1.1 Characteristics of the vessels by general region (2003-08)

Region	Boats	Share of total trips	Length (m)		Power (hp)		Hooks deployed (per set)	
			Mean	St Dev	Mean	St Dev	Mean	St Dev
North Queensland	12	13%	21.3	3.8	418.0	46.8	611.4	187.4
Central Qld	5	1%	19.9	2.6	347.2	131.0	1046.4	57.9
Mooloolaba	59	46%	22.1	3.4	368.0	126.2	1148.7	221.6
Brisbane and Gold Coast	7	4%	20.1	3.9	244.1	130.5	1024.0	184.4
Northern and Central NSW	13	5%	17.5	2.4	347.2	125.5	939.2	174.5
Sydney, Newcastle, Wollongong	15	10%	21.0	2.7	357.3	100.6	1039.9	135.9
Southern NSW	79	21%	21.7	5.4	349.5	145.3	996.0	254.7

1.2 Outline of the report

In the next section, the models are described. Two variants of a Dynamic State Variable Model (DSVM) were developed – one assuming a single species fisheries (or a single output given that revenue was the primary driver), and the other based on multiple outputs with differing price structures and spatial dynamics. A second type of model – the random utility model (RUM) was also developed as an alternative modelling approach. This was a more statistically based model than the DSVM, and used historic location choice behaviour to predict future behaviour under changing conditions.

In the results section, we describe the results from a number of different scenarios. These include closing particular areas to fishing entirely as well as different levels of hook penalties in these same areas. We examine the economic impact of these measures at both the fishery and port level. For the DSVM model, impacts for different sized vessels are also considered.

In the final sections, we compare the strengths and weaknesses of the different models, and draw conclusions about the relative costs and benefits of closures or incentive based management approaches. We also consider the implications for fisheries management, and also the implications of the move to ITQs on the set of analyses undertaken. In the future directions section, we identify a number of ways in which the models can be further developed to consider ITQs.

2. Need

In 2005, AFMA announced the *Eastern Tuna and Billfish Fishery Management Plan 2005,* which introduced a system of statutory fishing rights (SFRs) in the form of individual transferable effort quotas based on the number of hooks employed by each vessel, and a corresponding total allowable effort level (total number of hooks that can be deployed in the fishery). Although developed in 2005 (and amended in 2007), this management plan has only recently been fully implemented (2009). The statuatory fishing rights, and the allocation of effort that accompanies them, will be managed using Spatial Area Factors (SAFs). SAFs are multipliers that translate the actual amount of fishing effort expended, e.g. in thousands of hooks, into the amount of effort units that are deducted from an SFR holders allocation. The intent of these SAFs is to allow spatial management of the fishery, by providing incentives for fishers to work in areas with low SAFs and to avoid areas with high SAFs.

If used effectively, these SAFs may provide a mechanism for reducing many of the management conflicts in the fishery, such as catch of seabirds and turtles, depletion of target stocks in areas with high historic effort, and under-exploitation of high seas areas. However, in order to effectively apply the SAFs, AFMA will need to be able to determine the motivational effect of the SAF on fishers' location choices. Moreover, the SAFs will affect the total allowable effort (TAE) that is actually realized in the fishery in a given year, so not only will they affect individual fishers, they will also affect the performance of the fishery as a whole. It will be critical to be able to make some predictions about how the realized TAE will change, based on the structure of the SAFs in order to weigh alterative management options prior to implementing them.

3. Objectives

The specific objectives of this study relate directly to the needs identified above, in that it aims to assess the impacts of the hook decrementation system on the distribution of fishing effort and the economic impact on the fishery. To this end, the project aimed to:

- develop a statistical (multivariate logit) model to predict the distribution of fishing effort in the ETBF;
- develop a process (a state-dependent behavioural) model of effort allocation for an input managed fishery; and
- evaluate the impact of a series of SAF scenarios on the distribution of fishing effort in the ETBF using statistical and state-dependent behavioural models

4. Methods

4.1 Modelling fisher responses to spatial management changes

A critically important factor in developing a spatial management plan for any marine zone with an active fishing industry is a clear understanding of the dynamics of fishing effort, in particular addressing the question of how effort will be redistributed in response to a spatial management measure (Wilen 2004). For instance, if an area around a seabird breeding colony is closed to fishing to prevent incidental fishing mortality of the seabirds, it is of critical importance whether the fishers merely move to the edge of the closure area (where impacts might remain relatively high) or to another part of the fishery (producing a potentially different set of impacts). Different spatial management measures create different incentives, resulting in different responses by fishers. Assessing the effectiveness of the measure necessitates an ability to estimate the effects of the incentives created on fleet behaviour, and the subsequent impacts of this on the full set of management objectives (economic, conservation and social).

There is a substantial literature addressing the question of effort allocation in fisheries, and the more general question of state dependent foraging decisions in ecological systems (Mangel and Clark 1988, Houston and McNamara 1999, Clark and Mangel 2000) which we believe is relevant to conservation and management. This literature has taken at least two approaches: a retrospective approach based on statistical investigation of empirical data to ask about choice of fishing locations (Gillis *et al.* 1995a; Gillis *et al.* 1995b; Holland and Sutinen 1999, 2000; Smith 2002; Pradhan and Leung 2004) and a predictive approach, using mechanistic state dependent decision-making models to ask about future behaviour (Gillis et al. 1995a, 1995b). The latter include a number of spatial bioeconomic models that have been developed to model fisher response to changing conditions, particularly closures in the context of marine protected areas (Sanchirico and Wilen 1999; Smith and Wilen 2003; Dalton and Ralston 2004; Smith *et al.* 2009).

4.1.1 The statistical approach: Random Utility Models (RUMs)

The statistical approach generally derives the probability that a fisher applies effort in a given area based on the vessel characteristics (e.g. size, home port) and net returns from each area (using catch rates and distance). When applied to the total effort available by a fleet (i.e. summed up over the set of boats), one obtains an estimate of the overall allocation of effort. Most previously cited studies applied some form of the random utility model to model individual vessel behaviour, although more recent analyses suggest modelling behaviour at the fleet level may be more reliable in determining responses to novel conditions, including new management arrangements (Smith 2002).

Models of fisher location choice have largely been driven by the increasing use of marine protected areas. Closing areas to fishing forces fishers to either move elsewhere or cease fishing. However, assuming that the fishing effort previously expended in an area will evaporate following the area closure is, more than likely, a naive assumption. Instead, the effort will move to the next best available fishing ground.

A difficulty when examining location choice of fishers is that they are not homogeneous – vessels are based at different port locations (as well as fish in different locations), and fisher and vessel characteristics affects their cost structure. Hence, complications exist – expected economic returns are not only determined by revenue of catch (i.e. highest catch rates), but also by the costs associated with the fishing trip. Costs increase as distance travelled and steaming time increases. As a result, fishers are (within reason) able to select from which port they fish and where they land their catch to maximize the returns for species captured. In the modelling of spatial dynamics, several assumptions have been proposed. For example, the distribution of fishing effort could be assumed to move towards areas of highest catches (i.e. reflecting differences in revenues assuming constant costs) (Maury and Gascuel 1999), highest catch rates modified for distance to port (i.e. taking into consideration revenues and costs implicitly (Sampson 1991) or greatest profit (Bockstael and Opaluch 1984).

A method that allows for heterogeneity in both fishing activity and fisher characteristics is discrete choice modelling, or the random utility model (RUM) (McFadden 1974, 1981).[1] The key feature of the RUM is that it models discrete decisions with no requisite assumption of homogeneity amongst individuals. Rational decisions makers are assumed to make decisions that maximise their level of utility subject to any constraints. In the case of effort allocation in fisheries, utility is assumed to relate to profitability (subject to any constraints the fisher may face), and location choice is based on the expected profitability at each alternative location.

The method is probabilistic in nature in that the model estimates the probability of a fisher operating in a given area based on the characteristics of the area (e.g. average revenue per unit effort, distance from port etc) and the characteristics of the fisher. This probability is, therefore, specific to an individual fisher. The allocation of effort of the individual fisher to each area is estimated as the product of the total effort expended by the fisher and the probability that effort will be applied to each area. The total spatial effort allocation is derived by summing the effort in each area across all of the individual fishers.

Numerous studies have been undertaken in fisheries utilising a RUM approach to estimate fisher location choice (Bockstael and Opaluch 1984; Eales and Wilen 1986; Holland and Sutinen 1999; Curtis and Hicks 2000; Holland and Sutinen 2000; Smith 2002; Wilen *et al.* 2002; Hutton *et al.*

[1] Recently, increasing attention has also been paid to development of state dependent dynamic programming models to estimate fisher behavior (Gillis *et al.* 1995a; Gillis *et al.* 1995b; Costello and Polasky 2008; Poos *et al.* 2010). These have an additional advantage in quota based fisheries in that they also allow for the opportunity cost of using quota to be taken into account, so that the decision when as well as where to fish can be modelled (Costello and Polasky 2008).

2004; Pradhan and Leung 2004; Marchal *et al.* 2009). Most of these studies have employed multinomial logit techniques to estimate the model.

4.1.2 Dynamic State Variable Models (DSVM)

In contrast, state dependent decision-making models predict behaviour by optimizing an objective function, and determine which area best suits this behaviour given the set of incentives that exist (which may also depend on factors such as size, home port, distance to fishing grounds and expected catch rates). The approaches should produce similar outcomes if the statistical model includes the correct covariates and the process based model approximates the decision making process with good fidelity.

While both veins of investigation have merit, the mechanistic approach may be more useful in the context of estimating fishery responses to new management regimes, since it does not depend on historical patterns for its predictive power (Bue *et al.* 2008).[2] This is particularly relevant when the new regime creates an additional opportunity cost of fishing. For example, the introduction of a quota on catch or effort means that the decision to fish is a function not only by the relative catch rates in that time period, but also of the opportunity cost of using the quota now rather than later. That is, decisions need to be made not just on spatial allocation of effort, but also when effort is to be applied. This introduces the possibility of not fishing as being an optimal decision in some time periods, whereas this option would not be available in a statistical model based on pre-quota data. Effectively, the statistical models assume myopic behaviour. That is, location choice is based on the set of current or expected conditions, and does not take into account potential future conditions, including the potential future use of quota.

Despite commonly being used to examine the effects of marine protected areas in fisheries, the statistically derived approaches are unable to adequately address these elements of spatial management. For example, if a fishing area is removed (representing a closure), the statistical models will only predict one outcome – a proportional increase in effort in the remaining areas (by each individual fisher). However, the distribution of effort may change radically, and not in a proportional manner with changes in the available areas for fishing (Costello and Polasky 2008), for instance if fishers concentrate along the edges of a reserve in expectation of increased catches as is often observed (Goni 2006).

Developing mechanistic models requires more understanding of the factors driving the behaviour of the fleet, which we consider to be a good thing. However, this is often difficult to validate for situations not previously encountered (e.g. a new management regime). Despite this difficulty, mechanistic models can be based on sound economic logic, and, assuming fishers follow some form of economically rational behaviour (e.g. models based on individual profit maximization or

[2] Dynamic programming models in particular have been identified as being preferable for public policy analyses when new management regimes are to be introduced (Wolpin 1996) as they generally produce more plausible predictions out-of-sample (Burkhauser *et al.* 2004).

satisficing), can be used to estimate how fishers may respond to a broader range of incentives than possible using the statistical approaches. State dependent decision-making models require specification of the state(s) of interest for the analysis, for instance the capital reserves currently held by a fishing operator. The decision-making problem can then be expressed in terms of achieving an objective, e.g. achieving a maximum cash flow, in the context of that state, i.e. given the available investment capital.

4.2 The Dynamic State Variable Model (DSVM)

4.2.1 The single species model

We develop models for state dependent behaviour of individual fishing vessel types, translated into behaviour of the fleet, and implemented using stochastic dynamic programming (Mangel and Clark 1988; Clark and Mangel 2000; Costello and Polasky 2008). The models have increasing complexity, sequentially addressing questions of varying catchability, fleet behaviour driven prices, and seasonal availability in a spatially explicit context. The model is parameterised using data from the Eastern Tuna and Billfish Fishery (ETBF).

The ETBF longline fishery is characterized by vessels that tend to fall into discrete categories with respect to their capacity. Capacity is defined by the vessel's maximum speed, travel costs, cost per longline set (or shot), and the maximum time the vessel can remain at sea (largely influenced by the storage volume and/or freezing capacity of the hold), which in turn confers a maximum number of shots per vessel type per trip. Consistent with the operations of longline vessels (Campbell 2007), we assume that one shot equates to one day of the season, so that laying x shots requires x days. Since days will be lost due to weather conditions and social demands, there is an overall upper limit on the number of shots per fishing season.

<u>A model for state based decision-making in an effort quota fishery</u>

For purposes of model simplicity, we begin by considering a hypothetical single species fishery, operating out of one or two ports, and comprising 24 regions (Figure 4.1) with no stochasticity (Table 3.1).

The key parameters that characterize the habitat are

- $N_{i,j}(t)$: the abundance of fish in region with latitude i longitude j at day t of the current fishing season (determined exogenously)
- $q_{i,j}(t)$: the catchability of fish in region with latitude i longitude j at day t of the current fishing season (time variant since it may depend on changes in regulations, targeting, or environmental conditions (such as moon phase))
- $\delta_{i,j}$: the amount by which a vessel's effort allocation will be reduced (i.e. the penalty rate) if region with latitude i longitude j is fished (with one unit of fishing effort)

$D_{i,j}$: distance from region latitude i longitude j to port (assuming each region is 5 degrees square, and that each degree equates to 100 units of distance)

Table 3.1: Fishery parameterization

Quantity	Value	Detail
δ	1	Amount by which effort will be reduced in each spatial cell fished (constant for these examples)
Number of spatial cells	24	longitude 1 to 4, with 0 = port and 4 furthest offshore latitude 1 to 6, running south to north
Season length	120 time steps	Time steps are assumed to equate to days
Total effort units	100	Maximum effort (number of shots = fishing days) per vessel type per port in a season
Number of ports	2	Proxies for the southern (Mooloolaba) and northern (Cairns) ports of the ETBF Port location 1 (longitude index, latitude index): (0,2) Port location 2 (when used): (0,5)
Number of vessel types	3	See Table 3.2

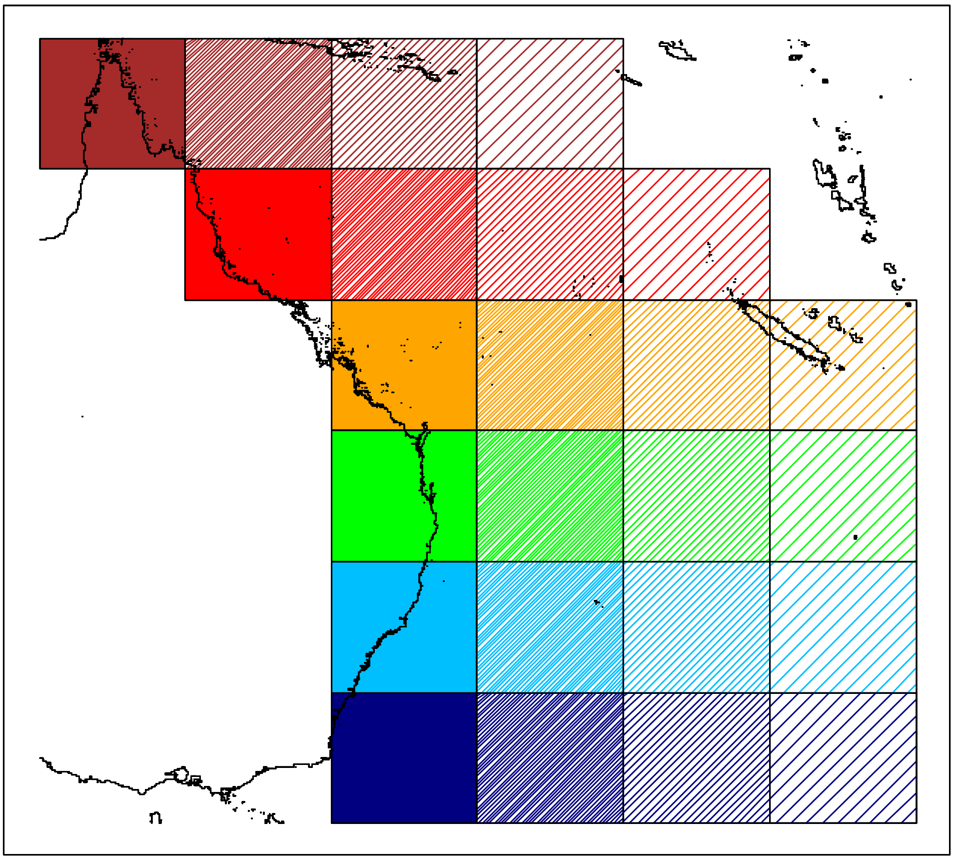

Figure 4.1. Map of Australia showing area of fleet operation and indicating regions, where each colour is used as a unique identifier of the regions in subsequent plots. Regions are indexed by (latitude code, longitude code).

We consider three different kinds of vessels (Table 3.2) characterized by:

v: the velocity of the vessel

x_{max}: the maximum number of longline shots allocated by a vessel in a fishing trip in any location, where a shot comprises one set and haul of longline gear (a fixed quantity defined according to vessel capacity)

ρ: the unit travel cost per vessel

E_{max}: the maximum number of shots per season allocated to each vessel.

Table 3.2 Summary of vessel characteristics

Vessel parameters	Vessel type 1	Vessel type 2	Vessel type 3
Maximum number of shots per trip, x	13	7	4
Relative velocity, v	6000	3000	2000
Relative cost per unit travel, ρ	3	2 (providing trip distance is less than 2/3 the maximum possible *)	1.4 (providing trip distance is less than 2/3 the maximum possible *)
Relative cost per shot, c	500	400	200

* *This distance was such that it did not exclude the central fish density from potentially being reached by lower capacity vessels even when this was further offshore.*

We set parameter values in a relative sense to consider three kinds of vessels. Vessel type 1 has a greater capacity in terms of shots per trip and velocity, but is more expensive per unit of travel and per shot. Vessel type 2 represents a moderate capacity vessel with correspondingly lower operating costs, while vessel type 3 is a low capacity, low cost vessel. This approximately reflects vessel types in the ETBF, in which faster vessels with greater shot capacity are typically more expensive in terms of travel and shot deployment.

We incorporated range limits for lower-capacity vessel types by assuming a step function for the cost-per-unit-travel. That is, if vessels travelled beyond their range (set as 2/3 the maximum possible distance within the area considered) cost increased sharply to prohibitively high levels (Table 3.2). This effectively imposed an absolute trip distance threshold to the lower capacity vessels, reflecting the inability of these smaller, lower-capacity vessels to undertake far-ranging offshore trips, despite their cost per unit travel being relatively low

Other parameters are

$p(t)$: the (species-specific) unit price for landed fish

c: the cost per shot

The state variable in our model is

$E(t)$: the effort (number of shots) remaining at time t in the season for a vessel

We assume a fishing season of length T days (i.e. $t = 1,\ldots..,T$). More specifically, T is defined as the first day of the last fishing trip of the season.

If a vessel visits region i,j and x shots are deployed on the visit at time t in the season, and its current remaining effort is $E(t)$, then the remaining effort is updated as

$$E(t + \frac{2D_{i,j}}{v} + x) = E(t) - \delta_{i,j}x \tag{1}$$

Equation (1) incorporates travel time both to and from the fishing region, and the time associated with setting x shots. Within the model, time is incremented by trip duration, that is, non-uniformly. For example, a 12-day trip may involve 4 days of travel on which no fishing occurs, and 8 days of fishing activity. The vessel would not be able to commence a new trip until the 13th day.

The profit associated with setting x shots in region with latitude i longitude j, for vessel type b operating out of port h, $\pi_{i,j}(t,x,b,h)$ is

$$\pi_{i,j}(t,x,b,h) = p(t)\cdot q_{i,j}(t)\cdot N_{i,j}(t)\cdot x - \rho_b \cdot D_{i,j} - c_b \cdot x \tag{2}$$

Since equation (2) is a linear function of the number of shots, x, it cannot account for risk aversion/taking, which we discuss at the end of the paper.

Vessels may only travel to one 5 degree-square location per trip, which is consistent with general observed fleet behaviour (Pascoe *et al.* 2010). In addition to choosing a fishing location, a vessel may remain in port at any given time. As such, there are effectively 25 “locations” (the 24 at-sea regions and the possibility of remaining in port), and ((24 x *Ntarg*) + 1) state spaces, where *Ntarg* is the number of targeting strategies. If a vessel remains in port, it is assumed to do so for one day, so that t is incremented by 1, after which the decision of where to go fish (or to stay in port) is made again. Staying in port allows a vessel to get “in phase” with the oscillating catchability (explained below) or “out of phase” with other competing vessels and thus avoids the expenditure of capital when catchability or price is low.

We model catchability as a spatially ubiquitous sine function, to approximate moon phase, which is consistent with the ETBF operators actively targeting swordfish around the full moon (Campbell and Hobday 2003) and parameterized so that one full cycle occurs approximately every 30 time steps across a 120 day season:

$q(t) = 0.1 \sin(0.2\, t)+1$

We let $F(e,t\,|\,b,h)$ denote the maximum expected profit accumulated between the current time t and the end of the season, T, for each vessel type b operating out of port h given that $E(t) = e$.

The maximum profit obtained for the final trip of the season for each vessel type, b, operating out of each port, h, is determined by where vessels fish and how many shots they lay. That is

(3) $$F(e,T\,|\,b,h) = \max_{i,j;x\le e}\left\{\pi_{i,j}(T,x,b,h)\right\}$$

If $x = 0$, vessels will stay in port.

For preceding times, $F(e,t\,|\,b,h)$ satisfies (Mangel and Clark 1988, Clark and Mangel 2000)

(4) $$F(e,t\,|\,b,h) = \max_{i,j;x\le e}\left\{\pi_{i,j}(t,x,b,h) + F(e-\delta_{i,j}x, t+\frac{2D_{i,j}}{v_b}+x\,|\,b,h)\right\}$$

Where $F(e-\delta_{i,j}x, t+\frac{2D_{i,j}}{v_b}+x\,|\,b,h)$ is the cumulative future profit, accumulated after the current trip. This total profit from the current point in time, to the end of the season, effectively represents the opportunity cost of fishing in that period.

Equation (4) is solved by backward iteration to find the optimal fishing region $(i,j)_{e,t}$ and the optimal number of shots $x^*(e,t)$ that yield the maximum accumulated profit. Since the equation is solved by backward iteration, the opportunity cost is effectively known with certainty (rather than based on expectations).

Once equation (4) is solved and the optimal set of fishing decisions is determined, forward projections can be used to calculate the total remaining effort, the accumulated value and the location choice associated with each trip. The solution depends upon the characteristics of the vessels (Table 3.2).

Stock structure and Dynamics

We assume that fish are distributed symmetrically about a core central spatial cell according to a bivariate normal distribution, so that the number of fish $N(i,j,t)$ at spatial location (i,j) is

$$N(i,j,t) = N_{\max}\cdot e^{\left(-\left[(i-i_P(t))^2/2.0\cdot\sigma_{iP}^2\right]-\left[(j-j_P(t))^2/2.0\cdot\sigma_{jP}^2\right]\right)}$$

where $N_{\max}$: total number of fish (= 10000000)

$i_P(t)$: latitude index with the highest density at the start of period *t*

$j_P(t)$: longitude index with the highest density at the start of period *t*

σ_{iP}: standard deviation about the central latitude index

σ_{jP}: standard deviation about the central longitude index

We model the movement in the location of the peak fish density at quarterly intervals during the fishing season, for a stock moving in an anticlockwise direction

t ≤30: $i_P = 4, j_P = 2$
30 ≤ t < 60: $i_P = 2, j_P = 2$
60 ≤ t < 90: $i_P = 2, j_P = 3$
t ≥ 90: $i_P = 4, j_P = 3$

We assume a constant stock size, *N*, through time, implying fishing does not affect local abundance. This is consistent with the hypothesis that for large pelagics, which are highly migratory (Brill *et al.* 2005), local replenishment occurs on a short time scale in a specific location.

Endogenously determined prices

Price is determined endogenously by treating price dynamics as a game (Clark and Mangel 2000):

1. We specify the number of ports and the vessel types operating from each port. Price is initially assumed to be constant, such that $p(t) = \overline{p}$, where $\overline{p}$ is (specified as a constant) set to $\overline{p}$ = 8.0 dollars based on a weighted average of yellowfin, albacore and billfish prices from 1996 to 2007.[3]

2. We solve Equation 4 for each vessel type from each port, using the candidate price trajectory *p*(*t*).

3. Given the optimal fishing locations and number of shots to lay for each vessel type from each port, we simulate forward in time to generate a time series of fish landings. We then generate a new price trajectory using these landings, assuming price is a function of the total volume V_t of landings by all vessels each time step, according to

(5) $$p(V_t) = \overline{p}\left(1 - f\left[\frac{V_t - \overline{V}}{\overline{V}}\right]\right)$$

where

f is the price flexibility[4]. For calculations, we set $|f|$ =0.1, consistent with other tuna modelling studies in the region (Hannesson and Kennedy 2009)

[3] Obtained from http://www.abare.gov.au/publications_html/afs/afs_09/09_FishStats.pdf

$\overline{V}$ is the mean catch per trip, calculated across all trips during the season for each Monte Carlo iteration

This generates a new price trajectory as a function of time, $p(t)$, as the simulated vessels return to port with their catches: $p(t) = p(V(t))$.

4. We repeat Steps 2 and 3 until the price trajectory that is used to solve the dynamic programming equation matches the one that comes out of the forward simulation. When these are identical, we conclude that the optimal response to a given trajectory of price has been achieved.[5] As a metric for comparison of the two trajectories we use

(6) $$S = \sum_{t=1}^{T} (p_b(t) - p_f(t))^2$$

where $p_b(t)$ is the price trajectory used in the SDP (initially, the constant vector $p(t)$) and $p_f(t)$ is the price trajectory generated by in the forward simulation via equation (5)

Stabilizing the Dynamic Game

For cases with more than one vessel type and/or port, we allow the game to deviate slightly from the optimal solution to prevent cycling and other undesirable behaviours in the solution method (Houston and McNamara 1999; Clark and Mangel 2000) by the method of errors in decision making. To do this, we assign a probability of choosing each region (latitude index i and longitude index j) proportional to its profit

(7) $$V(i,j,e,t,b,h) = \max_{i,j;x\le e}\left\{\pi_{i,j}(x,t,b,h) + F(e - \delta_{i,j}x, t + \frac{2D_{i,j}}{v_b} + x \mid b,h)\right\}$$

associated with each vessel type at each port at that point in the season, given the effort remaining.

If V^* is the profit at the optimal location for a given e and t we set

$$\Delta_{i,j}(e,t,b,h) = V^*(e,t,b,h) - V(i,j,e,t,b,h)$$

and then define the probability of fishing a particular area as

[4] Price flexibility is related to price elasticity of demand, except price flexibility relates to a price dependent demand curve (i.e. price adjusts to clear the quantity supplied) whereas price elasticity relates to a standard demand curve (quantity demanded adjusts based on the exogenous price) (Jaffry *et al.* 1999).

[5] An assumption in the model is that competition between vessels is not a major concern. The area of the fishery is relatively extensive and the fleet size is relatively small. Even within the cells, crowding is unlikely to occur in practice so anticipation of other vessel's locations is not considered a factor in the decision making process.

(8) $$P_{i,j}(e,t,b,h)=\frac{e^{-\Delta_{i,j}(e,t,b,h)/\sigma}}{\sum_{a=1}^{Nlat}\sum_{b=1}^{Nlong}e^{-\Delta_{a,b}(e,t,b,h)/\sigma}}$$

where σ is a tuning parameter that measures how important it is to be near optimal. If this is very large, then the vessels will choose locations at random. If it is very small, then all vessels will concentrate in the optimal location. For computations we use $\sigma = 1\text{x}10^3$ (noting that Δ ranges from 0 to ~$2\text{x}10^6$, but is generally of the order of $1\text{x}10^5$ in magnitude).

Using the rules for fleet behaviour given by the backward part of the game, the forward part now becomes a Monte Carlo simulation where areas visited are sampled randomly from a cumulative probability distribution given by equation (8). Price is then determined by taking the average catch across the Monte Carlo realizations for each area, for each vessel type, port and time step where that area is visited in that time step during any realization. This average catch is then summed over all vessel types and ports for each time step, and the resultant fed into equation (5).

We use three models of increasing complexity to illustrate the effect of fleet behaviour on prices, and seasonal availability in a spatially explicit context:

Case 1: 1 vessel type (Vessel Type 2), 1 port (Port location 1), oscillatory catchability.
Case 2: 3 vessel types, 2 ports, oscillatory catchability.
Case 3: 3 vessel types, 2 ports, oscillatory catchability, seasonally moving fish stock.

We used Case 3 to investigate how fishing locations change in response when opportunity costs are incorporated. This was achieved by repeating Case 3 with the following modifications: i) we treated each quarter of the season being independent by running the model 4 times assuming a 30-day season with an effort quota of 25 sets each time, and ii) with an effort quota of 25 across the 120 day season. The latter forces increased flexibility and hence introduces opportunity cost by reducing the total effort quota relative to the season length. The former is a control, in that the same amount of effort (25 sets) is spent across a 30 days, a duration that almost equates to the available effort (recalling that one set equates to one day of effort).

We investigated spatial manipulation (an effective MPA) by setting the effort decrement term, $\delta_{i,j}$, prohibitively high at 100.00 for region $i_P = 2, j_P = 2$, and comparing the resulting modelled distribution of effort with that which would have occurred if the effort formerly occurring in the closed area was redistributed in proportion to the existing effort in the remainder of the fishery. The area ($i_P = 2, j_P = 2$) selected to be closed was the one with the highest overall level of effort across the four quarters. Additionally, this effort was not concentrated at the end of the season, and so the results would not be confounded by any end-of-season effects.

Model performance: Vessel competition and fish movement

A single vessel type operating out of a single port fishing a stationary stock predictably made continual trips of very similar duration and effort, and the effort spent was close to or equal to the maximum permitted per trip. Fishing generally occurred in the area of highest density (the most profitable location given the vessel capacity), and occasionally in the adjacent inshore area(s). Although catchability was oscillatory, price remained constant over the season as a result of the relatively constant level of catch.

In case 2, individual decisions occur in the context of a competitive field of players (i.e. vessels with different capacities operating out of multiple ports) but the stock is stationary. Price now became highly variable due to the variation in the volume of landed catch throughout the season (Figure 4.2). In comparison to when it was the sole vessel type operating out of one port, vessel type 2 now has some short intervals in port during the season as a result of the variable price trajectory in combination with the oscillatory catchability (Figure 4.3). In general, however, vessel type 2 again undertook almost continual trips of very similar duration and effort, where effort spent was close to or equal to the maximum permitted per trip. In general, fishing occurred in the area of highest density (the most profitable location given the vessel capacity), and occasionally in the adjacent inshore area(s). The timing of trips, but not necessarily the location, was similar irrespective of port.

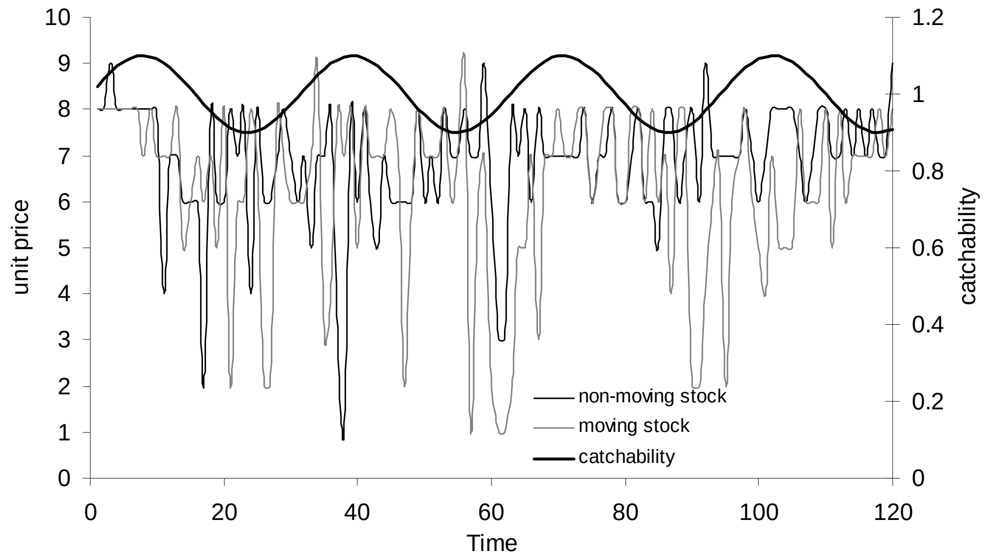

Figure 4.2. Overall price and catchability versus time, for i) case 2, aggregated across the 2 ports and 3 vessel types where fish are stationary, and ii) case 3, aggregated across the 2 ports and 3 vessel types, where fish are moving quarterly.

A similar pattern occurs for the highest capacity vessel (vessel type 1), albeit with less trips of longer duration, and a longer single interval in port. The lowest capacity vessel (vessel type 3), while making continual trips with effort close to or equal the maximum permitted per trip, was restricted to fishing inshore areas adjacent to the area of peak fish density and closer in latitude to port (Figure 4.3). This illustrates the trade off whereby a lower vessel speed and maximum effort level per trip, despite lower unit travel and setting costs, limit the ability of the vessel type to effectively target high fish densities offshore.

The introduction of quarterly fish movement highlighted the limitations of the lower capacity vessel types to fish in the area of highest fish density, particularly when this is further offshore. The price trajectory was again highly variable (Figure 4.2) All vessel types did show similar patterns, in of terms making continual trips with effort close to or equal the maximum permitted per trip, to those seen in case 2 (Figure 4.4). However, while vessel type 1 (the highest capacity vessel type) successfully tracked the area with the highest fish density throughout the fishing season, decreased vessel capacity leads to trips increasingly closer to the home port. Vessel type 2 operating from the southern port fished the area of highest fish density more successfully than the same vessel type operating out of the northern port, while effort for vessel type 3 was generally located inshore and closer to port relative to the peak fish density. As a result, the overall cumulative profit for the lower capacity vessels was slightly lower relative to case 2 where the central density was stationary at one of the more inshore locations (Figure 4.4). In general, total profit decreased with decreasing vessel capacity (Table 3.3).

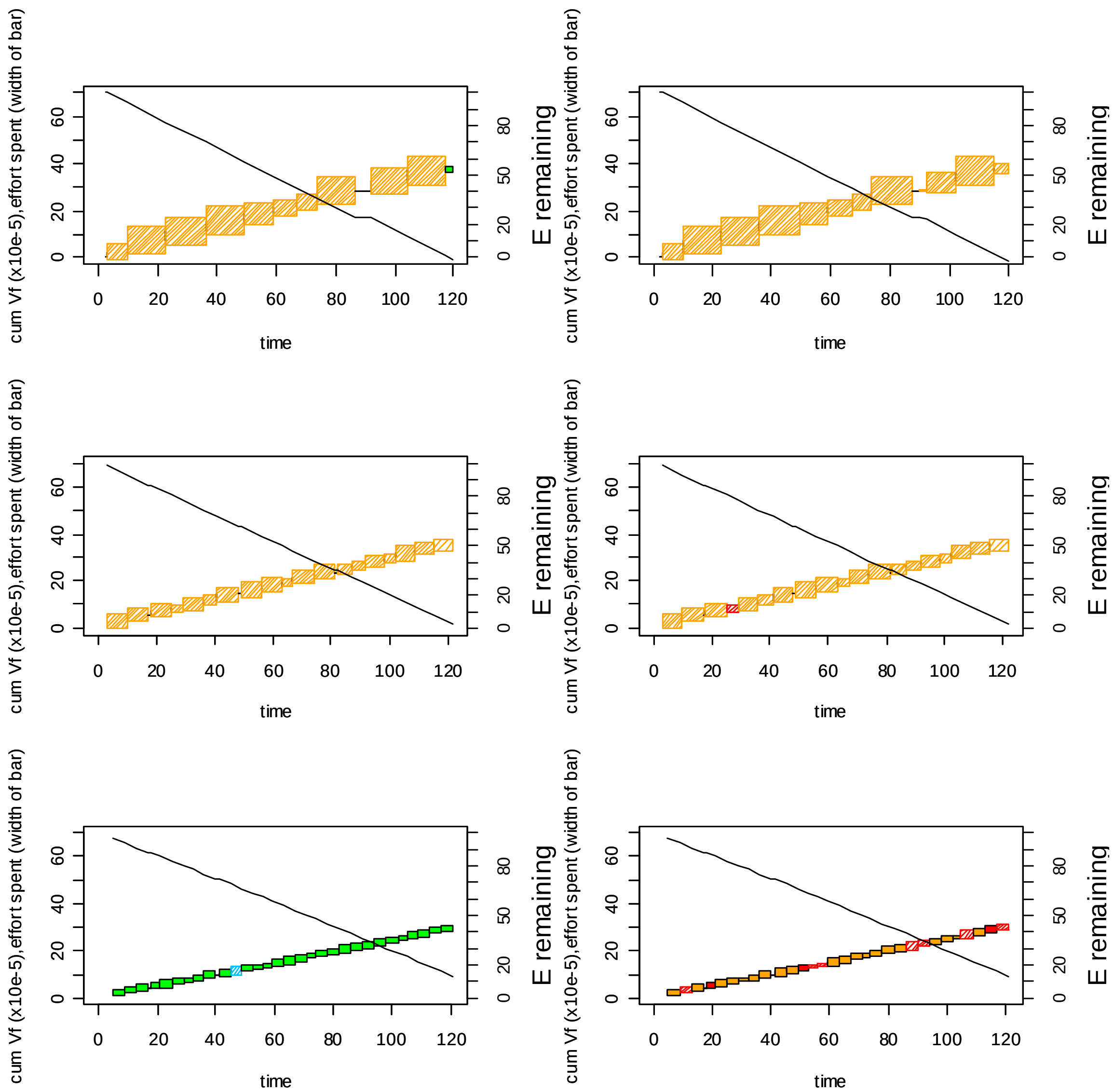

Figure 4.3. The time series of cumulative profit and remaining effort for each combination of 2 ports and 3 vessel types, where fish are stationary, for one Monte Carlo realisation. The height of the coloured bar equals the effort spent on the trip (with the cumulative profit at the midpoint), while the width equals the duration of the trip. The colour equates to the area visited on the trip, as per Figure 1. Top row = vessel type 1 (highest capacity vessel type); middle row = vessel type 2, bottom row = vessel type 3. Left panels = southernmost port; right panels = northernmost port.

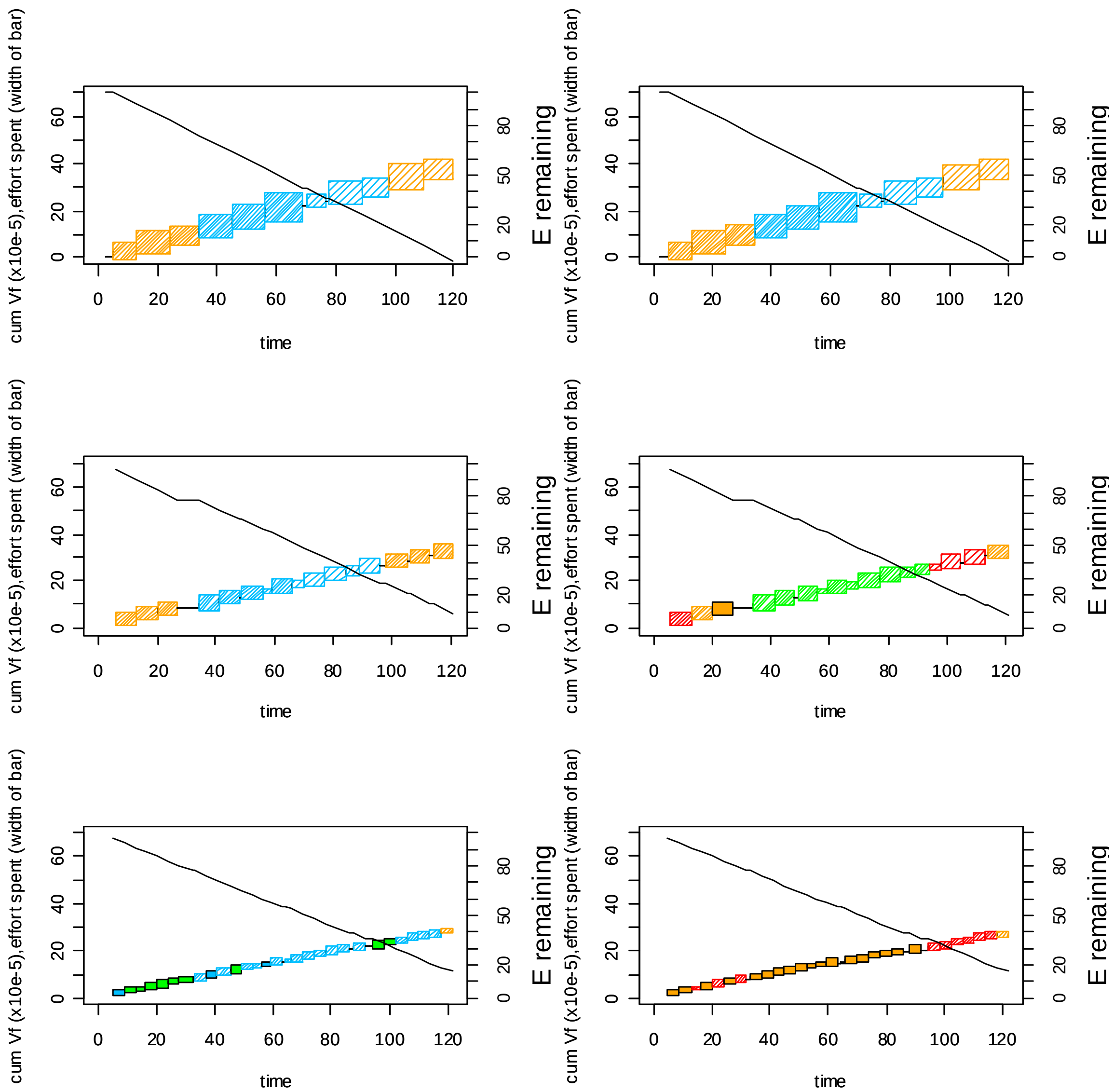

Figure 4.4. The time series of cumulative profit and remaining effort for each combination of 2 ports and 3 vessel types, where fish are moving quarterly, for one Monte Carlo realisation. The height of the coloured bar equals the effort spent on the trip (with the cumulative profit at the midpoint), while the width equals the duration of the trip. The colour equates to the area visited on the trip, as per Figure 1. Top row = vessel type 1 (highest capacity vessel type); middle row = vessel type 2, bottom row = vessel type 3. Left panels = southernmost port; right panels = northernmost port.

In summary, the key assumptions are utility is approximated by profit and that effort remaining at a given time in the season is an appropriate state variable. Assuming these are reasonable assumptions, the model forms a basis for investigating i) location choice in the context of considering opportunity cost, and ii) fleet responses to proposed spatial management options (i.e. that are "outside the data").

Table 3.3: Profit by vessel type and port for one iteration for scenarios illustrating opportunity cost and a spatial closure. Absolute profit is given for case 3, and all other profits are reported as percentages relative to case 3.

Model	Vessel type 1 Port 1	Vessel type 2 Port 1	Vessel type 3 Port 1	Vessel type 1 Port 2	Vessel type 2 Port 2	Vessel type 3 Port 2
Case 3	3.750 x10[6]	3.237 x10[6]	2.812 x10[6]	3.741 x10[6]	3.200 x10[6]	2.719 x10[6]
Quarter 1 independent	26%	28%	27%	25%	28%	28%
Quarter 2 independent	27%	29%	29%	27%	28%	27%
Quarter 3 independent	26%	29%	27%	27%	28%	25%
Quarter 4 independent	26%	27%	26%	26%	28%	28%
Quartered effort across whole season	40%	39%	39%	40%	39%	40%
Closure of area $i_P = 2, j_P = 2$	96%	112%	107%	96%	112%	108%

Model performance: opportunity cost and predicting fleet responses to spatial management

The previous cases indicated relatively even spreads of effort throughout the season, and indeed with an effort quota of 100 sets (≡ 100 days) in a 120 day season, there is little flexibility for quarterly preferences if the total quota is to be used. Opportunity cost was investigated via comparison of scenarios where a quarter of the prior effort quota (25 sets) was applied to each 30 day quarter of the season independently (i.e. in 4 separate stochastic dynamic models), with one where the same quartered effort quota of 25 sets was able to be freely applied across the 120 day season.

In the four independent $E_{max} = 25$, $T = 30$ models, one for each quarter of the fishing season, resulted in very similar distributions of effort to those observed in case 3. Profit levels for each were similar in magnitude (and when totalled, actually exceeded that from case 3 by about 8%) (Table 3.4), and showed little variation between vessel types and ports relative to case 3 (Table 3.3). However, when forced to incorporate the flexibility afforded by 25 units of effort across a 120 day season, the ability of the modelled fleet to consider opportunity cost was demonstrated by an overall profit level 43% greater than the highest profit obtained when the same level of effort was applied solely within any given quarter (Table 3.4), and this occurred irrespective of vessel type or port (Table 3.3). Within this scenario, the highest capacity vessel type is predicted not to fish in the third quarter of the season, when the peak fish density was located further offshore. The lower capacity vessel types fished in each quarter of the season, but the amount of effort dedicated to each quarter increased as the season progressed (Figure 4.5). We note that when the duration of the season was longer relative to the effort quota, the lower capacity vessels, in particular vessel type 3, and vessel type 2 operating out of the northern port, had a far higher incidence of fishing the areas of peak fish density than when E_{max} was set at 100 in the 120 day season (Figure 4.5 vs Figure 4.4))

Table 3.4. Total profit levels for one iteration for scenarios illustrating opportunity cost and a spatial closure.

Model	*Emax*	*T*	Total profit	Profit relative to Case 3
Case 3	100	120	1.946×10^{7}	
Quarter 1 independent	25	30	5.241×10^{6}	27%
Quarter 2 independent	25	30	5.406×10^{6}	28%
Quarter 3 independent	25	30	5.273×10^{6}	27%
Quarter 4 independent	25	30	5.184×10^{6}	27%
Quartered effort across whole season	25	120	7.720×10^{6}	40%
Closure of area $i_P = 2, j_P = 2$	100	120	2.033×10^{7}	104%

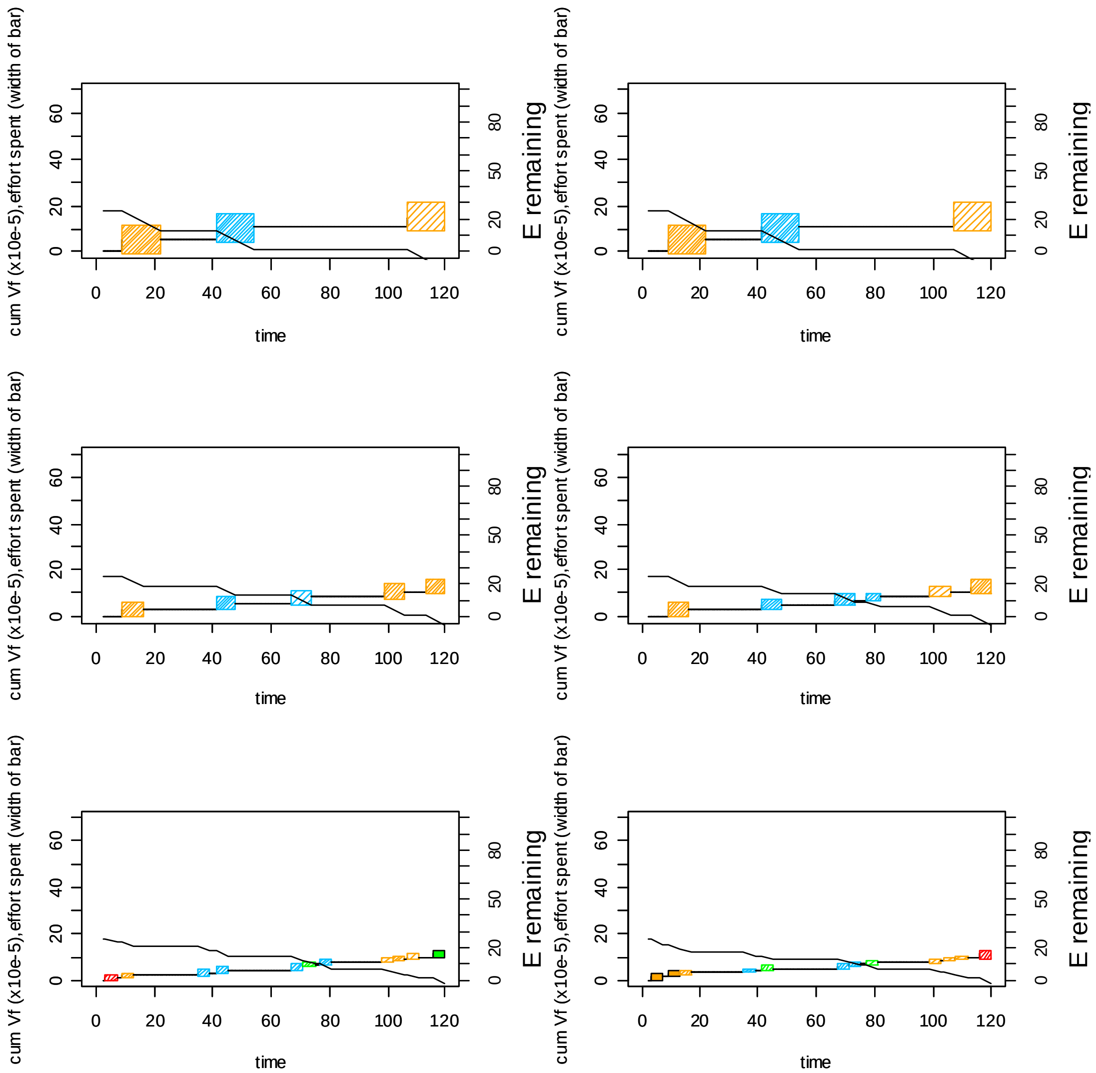

Figure 4.5. "Ribbon plot" showing time series of cumulative profit and remaining effort for each combination of 2 ports and 3 vessel types, where fish are moving quarterly and Emax =25, for one Monte Carlo realisation. The height of the coloured bar equals the effort spent on the trip (with the cumulative profit at the midpoint), while the width equals the duration of the trip. The colour equates to the area visited on the trip, as per Figure 1. Top row = vessel type 1 (highest capacity vessel type); middle row = vessel type 2, bottom row = vessel type 3. Left panels = southernmost port; right panels = northernmost port

As described above, closing the region ($i_P = 2, j_P = 2$) is likely to cause maximum perturbation to the dynamics of the fleet. Relative to the spatial effort distribution from case 3 (Figure 4.6), the effort that had occurred in region $i_P = 2, j_P = 2$ was redistributed, most typically to immediately adjacent cells, but not evenly among these, nor in proportion to the modelled effort patterns that were seen in this adjacent cells in the absence of the closure (Figure 4.7).

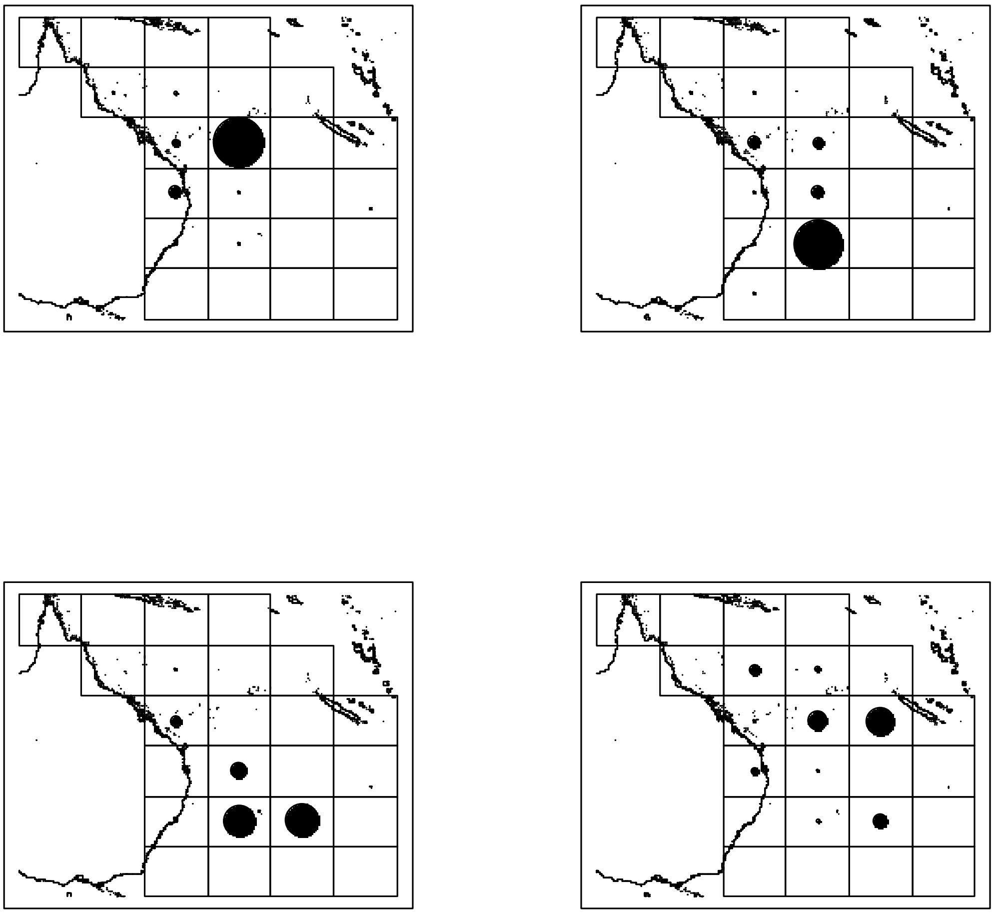

Figure 4.6 Spatial distribution and relative magnitude of total effort for case 3 (2 ports, 3 vessel types, quarterly fish movement) by quarter (each panel)

This relocation of effort occurred even when the peak fish density was not located in the closed area, but most notably in quarters 2 and 3, when the peak density was in this or the immediately adjacent offshore area. In the redistribution of effort to adjacent areas, the fleet gave preference to more inshore than offshore areas, presumably as a result of lower costs associated with travel. Moreover, effort was redistributed in part to areas that had not been previously shown to be exploited in the absence of the closure. This illustrates a key difference from approaches based on historical data, such as the statistical models discussed below in Section 2.5. The DSVM can predict fishing behaviours outside of those previously observed. Statistical approaches typically predict effort will be redistributed from a closed region proportionally among the remaining historically exploited regions. The stochastic dynamic model, however, redistributed the effort so as not to compromise profit, indeed yielding in an overall profit level that was ~4% higher for the closure scenario (Table 3.4). This increase was driven by relative increases in profit for the lower capacity vessel types; the highest capacity vessel type experienced 4% decreases in profit irrespective of port (Table 3.3).

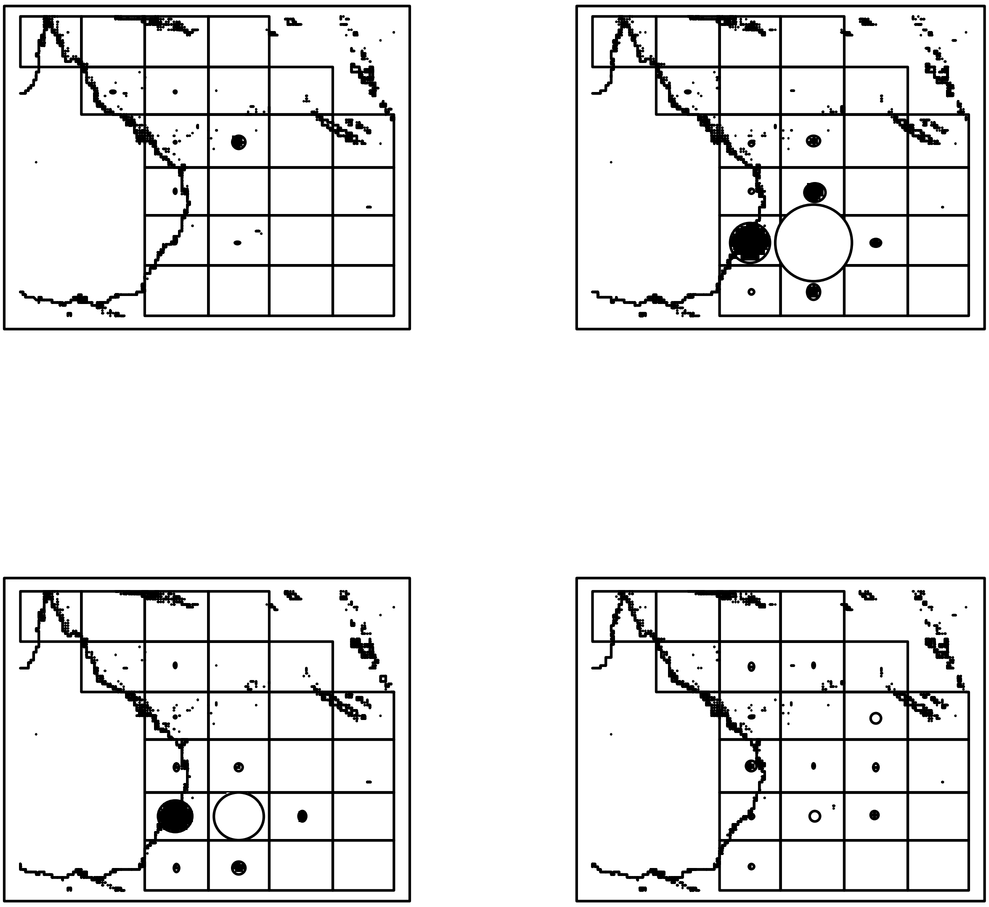

Figure 4.7: Spatial distribution and relative magnitude of the differences in effort for 2 ports, 3 vessel types, quarterly fish movement when region $i_P = 2, j_P = 2$ is closed, by quarter (each panel). Black circles indicate a relative increase in effort with the closure of region $i_P = 2, j_P = 2$ while open circles indicate a relative decrease.

4.2.2 The multispecies model

The multispecies version of the model extends the single species version to take into account the impact of changes in stock structure on profitability and hence targeting behaviour. Targeting behaviour is simulated by assuming that a given target strategy is associated with the expectation of a unique relative catch composition among the main target species. These relative expected proportions were applied to the species-specific catch equations. Although applied identically and having the same effect as the catchability term, they were kept as separate quantities. This was to reflect that the catchability term in the model was associated with availability (for example, oscillating according to moon phase), as opposed to targeting. Random errors could be imposed on these ratios, but for purposes of simplicity and initial evaluation, they were deterministic.

We defined multi-species targeting strategies as the desired relative proportions of each species for any given longline set. These proportions were obtained by undertaking cluster analysis on the set-by-set logbook data from 1997, 2003 and 2007. For this, we included all five main target species, as sets that may have similar catch compositions for the three species considered, may be targeting different non-included species and so should not be considered to be employing the same targeting strategy. We undertook a hierarchical cluster analysis using a Dirichlet distribution to represent the clusters. By dividing the resulting Dirichlet parameters by their sum, we obtained the expected proportions in the data, from which the likelihood of any data point could be calculated (Peel pers. comm.).

Due to limitations on the number of records that could be processed within the cluster analysis, we repeated the calculations for 4 random subsets of the data, each of which comprised 600 random sets from each of the three years. For each data subset, we obtained sets of 1-13 clusters and, based on the AIC value for each, we determined that 11 clusters was statistically optimal (based on Burnham and Anderson, an AIC value is not distinguishably different if the difference between values is less than 10. While our AIC values were never <10, the difference was consistently smallest across the 4 subsets of data for 11-12 clusters).

The results from the different data subsets were qualitatively similar so one subset was chosen as being representative. The clusters from this subset were then used to statistically assign a cluster to each set in the data. This was done using a multinomial with the expectations of the Dirichlet parameters to find the most likely cluster for each longline set.

Clusters were interpreted as being separate targeting strategies that may or may not also be associated with a given habitat, and that are able to be actively chosen by fishers. Two of the eleven clusters comprised predominantly bigeye tuna and striped marlin respectively, and so were excluded from this model as we did not consider these species. Five of the remaining 9 clusters were aggregated into two groups, since one group of three clusters and one of two clusters were qualitatively similar and combining these considerably reduced the state space (Table 3.5). The resultant 6 clusters were included in the state space when solving the dynamic programming equation, so that the total number of states was 24 areas x 6 targeting strategies + 1 state of remaining in port = 145 states.

Table 3.5: Relative proportions of each species, together comprising the 6 clusters corresponding to 6 targeting strategies

Cluster/target strategy	YFT	ALB	SWO
1	0.04	0.94	0.02
2	0.92	0.05	0.03
3	0.34	0.55	0.10
4	0.12	0.11	0.77
5	0.13	0.44	0.43
6	0.37	0.24	0.39

When solving the dynamic programming equation in the backwards part of the model, it was assumed that the effort was allocated exactly according to the targeting strategy, with the resulting catch at any time *t* for vessel type *b* operating out of port *h* being:

$$\sum_{s=1}^{n} C(t,b,h,s) = \sum_{s=1}^{n} r(w,s) \cdot q_{i,j}(t,s) \cdot E(t,b,h) \cdot N_{i,j}(t,s)$$

where *r* is the proportion of species *s* associated with targeting strategy *w*

q is the catchability of fish in region with latitude *i* longitude *j* at day *t* of the current fishing season (time variant as it may depend on changes in regulations, targeting, or environmental conditions (such as moon phase)

$E(t,b,h)$ is the effort (number of shots) remaining at time *t* in the season for a vessel type *b* operating out of port *h*

$N_{i,j}(t,s)$ is the abundance of fish of species *s* in region with latitude *i* longitude *j* at day *t* of the current fishing season (determined exogenously)

To obtain random variability on the realized catch composition, we used a binomial random variable. For each species, we obtained a new relative catch proportion by sampling randomly from a cumulative density function of the binomial distribution, assuming a pool of 100 and a success probability equal to the relative proportion of that species in the catch composition according to the cluster/targeting strategy.

<u>Model parameterization: movement and relative abundance/availability</u>

We modelled changes in relative abundance, together with the movement in the location of the peak fish density at quarterly intervals during the fishing season. This was assumed to be constant irrespective of year. Generalised linear modelling (GLM) was used to standardize for the effect of confounding factors (environmental and targeting practices) and obtain seasonal proxy abundance indices for each species in each year and quarter, for each of the 24 5-degree squares that together constituted the region of the ETBF considered by the model (Figure 4.1). Set specific data was obtained from 1997-2007. Using the results from cluster analysis, we undertook CPUE standardization only on those sets whose catch compositions showed a predominance of the target species

GLMs were fitted to log transformed catch-per-unit effort data incorporating main effects for year, area (in 5-degree squares), quarter of the year (January-March; April-June; July-September; October-December), Southern Oscillation Index, moon phase (expressed as a numeric value from 1 to 24, where 1=new moon, 24=full moon), the number of hooks per basket (which is a proxy for fishing depth), the number of light sticks used on the set, the bait type, the time at which setting commenced (24 one-hour periods). We also included interaction terms for year by area and quarter by area.

Using the fitted GLM, the effect of the environmental and targeting variables was removed so that the standardised CPUEs were a function of year, area, and quarter, and the interactions between year and area, and quarter and area. These yielded proxy indices of species availability by area and quarter for each year of interest, and this was multiplied by $Nmax(s)$, the hypothetical maximum total number of fish of species s (= 1×10^7) to yield approximations for spatial and seasonal abundance in the model. The only exceptions were where anomalously large standardised abundances were predicted in data-poor year/area/quarter combinations. In these instances the proxy abundance was reduced to zero.

We assume a constant underlying stock size, N, through time, implying fishing does not affect local abundance. This is consistent with the hypothesis that for large pelagics, which are highly migratory (Brill et al. 2005), local replenishment occurs.

Key parameters, state space and fleet dynamics

The key parameters, state space and fleet dynamics are identical to those described for the single species model, with the only, obvious exception being that, where relevant, these become target-species-specific, and incorporating targeting strategies. In particular,

- $N_{i,j}(t,s)$ is the abundance of fish of species s in region with latitude i longitude j at day t of the current fishing season (determined exogenously)
- $q_{i,j}(t,s)$ is the catchability of fish of species s in region with latitude i longitude j at day t of the current fishing season (time variant as it may depend on changes in regulations, targeting, or environmental conditions (such as moon phase))
- $p(t,s)$ is the (species-specific) unit price for landed fish

The profit associated with setting x shots in region latitude i longitude j, for vessel type b operating out of port h , and using targeting strategy k, $\pi_{i,j,k}(t,x,b,h)$ is obtained by summing across the various species, weighting their abundance by their price, catchability and the targeting strategy employed:

$$\pi_{i,j,k}(t,x,b,h) = \sum_s (p(t,s) \cdot r(k,s) \cdot q_{i,j}(t,s) \cdot N_{i,j}(t,s) \cdot x) - \rho_b \cdot D_{i,j} - c_b \cdot x$$

where $r(k,s)$ is the relative proportion of fish of species s associated with targeting strategy k

As in the single species model, we model catchability for each species as spatially ubiquitous sine functions, derived as simplified descriptions of fitted relationships between the standardized CPUE indices and moon phase. For swordfish, targeted on the full moon (Campbell and Hobday 2003), the sine function was parameterized so that one full cycle occurs approximately every 30 time steps. Albacore and yellowfin tuna showed lower amplitude and slightly lower periodicity within the lunar cycle (Table 3.6).

$$q(t) = \alpha \sin(\beta t)+1+ \gamma$$

where γ controls the relative magnitude of the catchability and can be increased for one species relative to another. We explore two scenarios, one corresponding to the year 2007 when the fishery is considered to have been catching relatively high numbers of albacore, and a second corresponding to 2004 where the catchability of swordfish was relatively high relative to its level in other years (Table 3.6).

Table 3.6: Parameter values for catchability equation

	Α	β	Γ
YFT	0.173	0.3	0
ALB	0.318	0.3	2 (2007: model)
SWO	0.383	0.2	0.5 (2004 model)

As with the single species model, we let $F(e,t\,|\,b,h)$ denote the maximum expected profit accumulated between the current time t and the end of the season, T, for each vessel type b operating out of port h given that $E(t)=e$. The maximum profit obtained for the final trip of the season for each vessel type, b, operating out of each port, h, is determined by where vessels fish and how many shots they lay.

(9) $$F(e,T\,|\,b,h) = \max_{i,j,k;x\le e} \{\pi_{i,j,k}(T,x,b,h)\}$$

If $x = 0$, vessels will stay in port.

For preceding times, $F(e,t\,|\,b,h)$ satisfies (Mangel and Clark 1988, Clark and Mangel 2000)

(10) $$F(e,t\,|\,b,h) = \max_{i,j,k;x\le e} \left\{\pi_{i,j,k}(t,x,b,h) + F(e-\delta_{i,j}x, t+\frac{2D_{i,j}}{v_b}+x\,|\,b,h)\right\}$$

where $F(e-\delta_{i,j}x, t+\frac{2D_{i,j}}{v_b}+x\,|\,b,h)$ is the cumulative future profit, accumulated after the current trip. This total profit from the current point in time, to the end of the season, effectively represents the opportunity cost of fishing.

Equation (10) is solved by backward iteration, which also determines the optimal fishing region $i^*(e,t)$, optimal targeting strategy, and the optimal number of shots $x^*(e,t)$ (i.e. that yield the maximum accumulated profit).

Once equation (10) is solved, forward projections can be used to calculate the remaining effort, the accumulated value and the location/targeting choice. The solution depends upon the characteristics of the vessels (Table 3.2).

Stock structure and Dynamics

We assume that each species of fish, *s*, is distributed according to the proxy abundance indices obtained using GLM, and that these indices are multiplied by *Nmax*(*s*) to yield the number of fish of each species, $N_s(i,j,t)$, at spatial location (i,j) at any time *t* during the season, where $N_s(i,j,t)$ is updated each quarter according to the GLM indices.

We assume a constant stock size, *N*, for each species in any given quarter (based on inferred relative species availability by quarter), implying fishing does not affect local abundance. This is consistent with the hypothesis that for large pelagics, which are highly migratory (Brill et al. 2005), local replenishment occurs on a short enough time scale in a specific location.

Endogenously determined prices

As with the single-species model, for each species, species-specific price was determined endogenously by treating price dynamics as a game (Clark and Mangel 2000). A forward-and-backward (FAB) approach was used as described for the single species model, except that price is now species-specific; $p(t,s)$, and so price is a function of the species-specific volume $V_t(s)$ of landings by all vessels each time step. As such, the new price trajectory is generated according to

$$p(V_t,s) = \overline{p(s)}\left(1 - f\left[\frac{V_t(s) - \overline{V(s)}}{\overline{V(s)}}\right]\right)$$

where

$\overline{p(s)}$ is the mean price for species *s*, specified as a constant, and taken from average historical prices in the year of interest, as obtained from ABARE (ABARE 2009a).

f is the price flexibility, as for the single species model. For calculations, we set $|f|$ =0.1, consistent with other tuna modelling studies in the region (Hannesson and Kennedy 2009)

$\overline{V(s)}$ is the mean catch per trip, calculated across all trips during the season for each Monte Carlo iteration

This generates a new species-specific price trajectory as a function of time, $p(t,s)$, as the simulated vessels return to port with their catches: $p(t,s) = p(V(t,s))$.

Stabilizing the Dynamic Game

This is done in the same manner as for the single species model, that is, by the method of errors in decision making (Houston and McNamara 1999, Clark and Mangel 2000). The probability of each region (latitude index *i* and longitude index *j*) being visited and each targeting strategy, *k*, being used, is assigned to be proportional to the profit:

$$V(i,j,k,e,t,b,h)=\max_{i,j;x\le e}\left\{\pi_{i,j,k}(x,t,b,h)+F(e-\delta_{i,j}x,t+\frac{2D_{i,j}}{v_b}+x\mid b,h)\right\}$$

associated with each vessel type at each port at that point in the season, given the effort remaining.

If V^* is the profit at the optimal location for a given *e* and *t* we set

$$\Delta_{i,j,k}(e,t,b,h)=V^*(e,t,b,h)-V(i,j,k,e,t,b,h)$$

and then define

$$p_{i,j,k}(e,t,b,h)=\frac{e^{-\Delta_{i,j,k}(e,t,b,h)/\sigma}}{\sum_{a=1}^{Nlat}\sum_{b=1}^{Nlong}\sum_{c=1}^{Nt\arg}e^{-\Delta_{a,b,c}(e,t,b,h)/\sigma}}$$

where σ is a tuning parameter that measures how important it is to be near optimal. If this is very large, then vessels will choose locations at random. If it is very small, then all vessels will concentrate in the optimal location. For computations we use σ = 5x10^6 (noting that Δ ranges from 0 to ~2x10^6, but is generally of the order of 1x10^5 in magnitude). We now proceed to stabilise the dynamic game as for the single species model.

4.3 The random utility model

As in most economic-based choice models, utility is assumed to derive from an individual's choice, while the choice itself is assumed to be made on the basis of the characteristics of the option chosen. Different decisions of individuals are treated as independent over time (Smith 2002). The individual choice (and the derived utility) is assumed to have both a deterministic component and a stochastic error component (thereby giving the term "random utility model"). Utility is typically defined as a (linear) combination of a set of explanatory variables that together are surmised to form (for the most part) the non-random components of the utility, and a stochastic error component:

$$U_{ij} = \beta_j z_{i,j} + \varepsilon_{ij} \qquad (1)$$

where for a given person time-event, *i*, (such as a fishing trip) choice *j* (i.e. fishing location) is made. The explanatory variables z_{ij} can be comprised of attributes of the choice, x_{ij}, and characteristics of the individual, w_i, while β_j is the parameter vector to be estimated.

The basic multinomial logit model assumes that all choices are independent of irrelevant alternatives (IIA). However, alternatives in close proximity to each other most likely share the same, or similar, characteristics, and the IIA assumption is likely to be invalid. The nested multinomial logit (NL) model overcomes this by partially relaxing the IIA assumption through allowing for some correlation between sub-sets of alternatives (Hensher *et al.* 2005). The NL is a structural model of the interdependent decisions of where to fish (Smith 2002). Several levels of choice may be specified, such as general fishing zone and then area within that fishing zone., and the NL allows for different variances at these different nodes (Smith 2002).

The choice probability of the nested multinomial logit model is defined as the conditional probability of area *j* in zone *k* (i.e. $j|k$) *j* is given by

$$\Pr(j|k) = \frac{\exp(\beta_j' z_{j|k})}{\sum_{j \in k} \exp(\beta_j' z_{j|k})} = \frac{\exp(\beta_j' z_{j|k})}{\exp K_k} \qquad (2)$$

and

$$K_k = \ln\left[\sum_{j \in k} \exp(\beta_j' z_{j|k})\right] \qquad (3)$$

where K_k is the inclusive value for zone *k*, representing the composite utility of the choices within the branch (Holland and Sutinen 1999).

The probability of choosing a particular zone *k* is given by

$$\Pr(k) = \frac{\exp(\tau_k K_k)}{\sum_k \exp(\tau_k K_k)} \qquad (4)$$

where τ_k is the inclusive value variable relating to zone *k*. The unconditional probability of fishing in any particular area *j* is given by $\Pr(k) \cdot \Pr(j|k)$

4.3.1 Data

Individual shot level logbook data were available covering the period 2003 to 2008. From this, information was available on catch by species, fishing area (latitude and longitude), trip length, as well as vessel characteristics (vessel length, power, hooks deployed per shot). Only vessels registered to ports in New South Wales (NSW) or Queensland were included in the analysis. Vessels either fished for one, two or three days per trip (steaming time was not included in the data set, only active fishing time), with most trips being of 2 fishing days duration (Table 2). Only one shot per day was taken. Distance (great circle nautical miles) to port was estimated for each fishing trip location (defined by the lat and long of each shot). Once in an area, distance travelled in multi-shot trips was relatively small (Table 3.7).

Table 3.7 Distance to home port by trip length

		Distance travelled (nautical miles)		
trip length (days)	Number of trips	Home to first shot	First to second	Second to third
1	6,710	193.41		
2	18,554	263.81	31.77	
3	1,631	135.89	27.02	25.01
Total	26,895			

Data were aggregated to a trip level, with the number of days fished each trip retained as a variable. The total distance travelled (return trip) was used as a measure of distance to allow for multi-day trips.

Price information for the key species was derived from ABARE fisheries and commodity statistics (ABARE 2008, 2009a, b). Weekly diesel price information was available from the WA Fuelwatch website.[6] While these data related to Western Australia, a consistent series of east coast data at a weekly level were not available. The diesel fuel prices were adjusted by the off-road rebate ($0.381 per litre) in place over the period of the data, and the weekly price series converted to an index. All prices were converted to real (2007-08) values using the consumer price index.[7]

For the purposes of the model, each trip was allocated to a 1^{o} square location (an area of 60x60 nautical miles (NM)) based on their latitude and longitude. For trips that straddled two or more areas, the middle area was used to represent the trip (this happened very rarely as most trips between shots were less around 30 NM, see Table 3.7). Areas with low observed effort levels (see Figure 4.8) were amalgamated with adjacent low effort areas, resulting in a total of 72 fishing areas.

[6] www.fuelwatch.wa.gov.au/

[7] www.ausstats.abs.gov.au/ausstats/meisubs.nsf/0/0C4B698A7E84A0D6CA25765C0019F682/$File/640101.xls

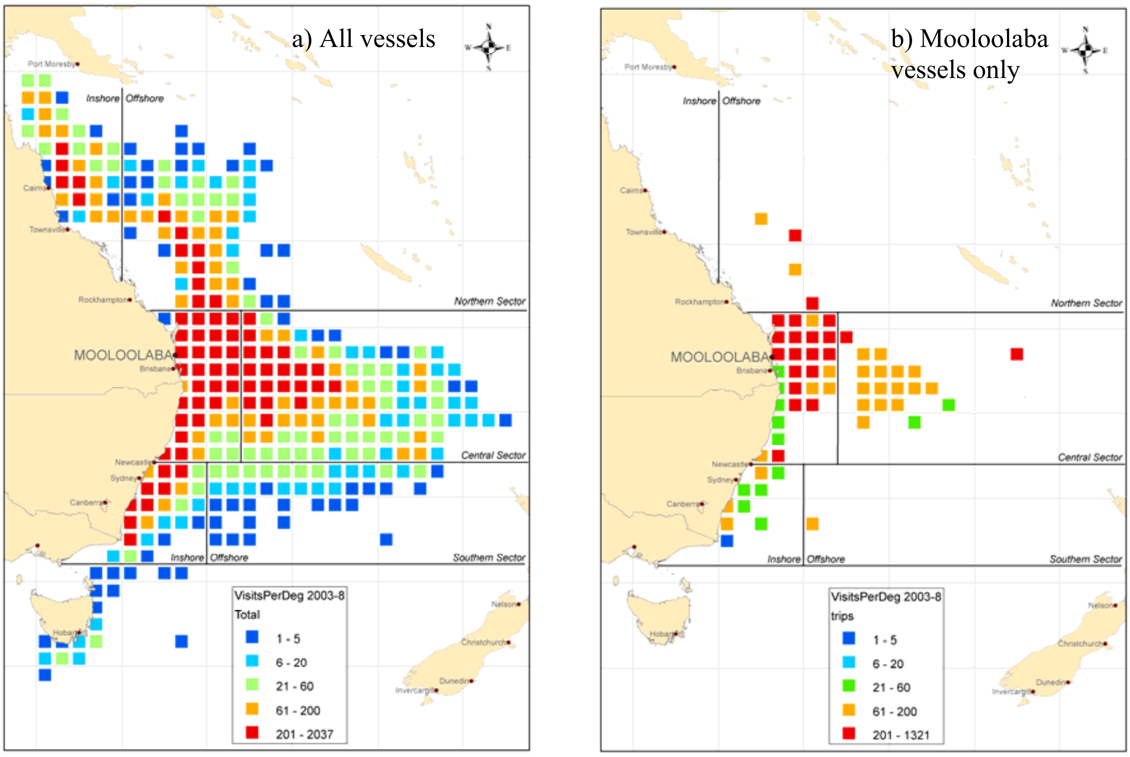

Figure 4.8. Distribution of total fishing days, 2003-08 (a) all vessels; (b) Mooloolaba vessels

As adjacent areas are likely to be similar in characteristics (e.g. distance from port and possibly catch distribution), it is likely that all alternatives are not independent, and the choice of where to fish will be hierarchical (i.e. general area first then a specific location within that area). For the purposes of the econometric analysis, the fishery was also split into six zones (Figure 4.8), although given the low number of observations in the north inshore and offshore these were eventually combined into a Northern zone.

The key area variables used in the analysis were average value per hook, and the average distance to the home port multiplied by the fuel price index as a proxy indicator of fishing costs (on the assumption that both distance and fuel prices influenced the decision). The average distance of vessels fishing rather than the distance to the mid point of the area was used as this better reflected where the activity was taking place within the area. A second variable was estimated by dividing the average distance (multiplied by fuel prices) by the average number of days fished per trip by vessels operating in those areas, reflecting that distances further away may be compensated partially by a longer fishing trip (Holland and Sutinen 1999). The level of fishing effort (in number of trips) in each cell in the previous week and the previous year were also derived on the basis that fishers may use the activities of others in shaping their expectations.

The average value per hook (VPH) deployed from each trip was estimated using the price and catch data, and the average of these for each area for each week was used to represent the expected revenue from fishing in a particular location. As the model estimation is based on expected, rather than realised, revenues, the values for the preceding week, and also same week in the preceding year, were used in the analysis. Where no fishing activity took place in a given week, the minimum value observed over the whole period of the data was used. The coefficient of variation in VPH was also included as a variable to capture any risk seeking or aversion behaviour. A negative parameter value on this variable would reflect risk aversion, while a positive parameter would reflect risk seeking behaviour (Holland and Sutinen 1999).

The key individual vessel characteristics included in the model involved the size of the vessel and its previous fishing activity. Smaller vessels are believed less likely to undertake trips offshore than their larger counterparts, mainly as they have a lower capacity for storage and lower fuel reserves. To allow for this, the distance variable (multiplied by price) was divided by the length of the vessel, with an a priori expectation that the sign of the coefficient for this variable would be negative (i.e. the probability of fishing further from port decreases as the vessel length decreases, and vice versa). Many other studies have found that past behaviour is also a key factor in determining future effort allocation (Holland and Sutinen 1999, 2000; Hutton *et al.* 2004). The location fished in the previous week and also in the same week the previous year was included for each vessel as dummy variables. This resulted in the loss of data for weeks in which the vessel did not fish the previous week,[8] or in that week the previous year. Also, the first year (2003) of the data was excluded as a lag of one year was required. The final data set used for the analysis involved 3472 trips.

4.3.2. Estimated model parameters

<u>The Mooloolaba-only model</u>

The analysis was initially undertaken for the Mooloolaba fleet only in order to test the modelling system and test the relevance of the key parameters.

The model was estimated as a nested multinomial logit model. Fishing areas were aggregated into 5 zones based on the aggregate effort allocation of all boats across the fishery: northern, central inshore, central offshore, southern inshore and southern offshore.[9] The inclusive value relating to the central inshore zone was normalised to 1 to avoid identification problems (Hensher *et al.* 2005). A normal multinomial specification of the model was also tested, with the nested model having a lower AIC score. Further, the inclusive variable values were significantly greater than zero and significantly less than or equal to 1 (Table 3.8), suggesting a nested specification is more appropriate (Hensher *et al.* 2005).

[8] Other studies have used a dummy variable to identify data for vessels that did not fish the previous week (Holland and Sutinen 1999, 2000).
[9] The last branch is degenerate as it contains only one alternative. As the alternative is specified at level two, the scale parameter is free to vary (Hensher *et al.* 2005).

Table 3.8. Estimated NL model parameters

Variable	All variables Coeff	St. error	Coeff/ St.Er.	P[Z>z]	Excluding "habit" variables Coeff	St. error	Coeff/ St.Er.	P[Z>z]
Utility model								
VPH Week-1	0.188	0.007	27.26	***	0.188	0.007	27.27	***
VPH Year-1	0.041	0.005	8.57	***	0.041	0.005	8.56	***
Density Week-1	0.171	0.007	24.82	***	0.171	0.007	24.84	***
Density Year-1	0.017	0.009	1.83	*	0.017	0.009	1.85	*
Coeff. Variation	0.770	0.071	10.85	***	0.772	0.071	10.88	***
P*distance	0.020	0.001	16.03	***	0.020	0.001	16.03	***
P*distance/days	-0.002	0.001	-1.91	*	-0.002	0.001	-1.90	*
P*distance/length	-0.418	0.024	-17.26	***	-0.418	0.024	-17.26	***
Fished last week	-0.217	0.166	-1.31					
Fished last year	-0.005	0.153	-0.03					
Inclusive values								
North	1.026	0.024	42.95	***	1.027	0.024	43.02	***
Central inshore	1.000				1.000			
Central offshore	0.900	0.015	60.66	***	0.901	0.015	60.75	***
South inshore	0.613	0.023	26.84	***	0.613	0.023	26.87	***
South offshore	0.343	0.096	3.56	***	0.345	0.096	3.60	***
Model diagnostics								
Chi squared		6763.9				6762.1		
Log likelihood		-12461.5				-12462.4		
McFadden Pseudo R-squared		0.213				0.213		
AIC		7.1864				7.1857		

*** significant at 1% level; ** significant at 5% level, * significant at 10% level

The model was initially run with location-specific constants. However, these were individually (and jointly) not significantly different from zero so were excluded from the subsequent models. Most of the parameters were significant, at least at the 10% level with many at the 1% level, with the exception of the variables representing location choice in the previous week and year (Table 3.8). In many previous studies, location choice is heavily influenced by previous fishing locations. These studies have largely been based on trawl fisheries exploiting demersal finfish. While the main swordfish species targeted in the fishery have a residential association with seamounts, the main tuna species in the ETBF are migratory, largely following thermal eddies in the ocean.[10] These eddies follow a similar, but not identical pattern from year to year in terms of both timing and location. Further, fishers are able to obtain reliable information on where these eddies are at any point in time, so past fishing activities (generally referred to as "habits", (Holland and Sutinen 2000)) are less important in this fishery than in others. The fishery is also dynamic in other ways: relative prices between species have changed over the period of the data, while the availability of individual species varies considerably inter-annually, changing the value per hook. Given these changes, best locations in the past may not be as valuable in the future, and fishers may place

[10] Sea surface temperature is likely to influence the fishers' expectations of catches and revenues, and would be a useful additional variable to include in the model. Such data were not available at the time of the analysis.

little value on their past behaviour.[11] Excluding these variables slightly improved the model (in terms of the AIC).

All the coefficients had the *a priori* expected signs. The utility (and hence the probability) of fishing in an area increased the higher the VPH in the previous week and year, and distant locations had a lower probability of being fished by smaller vessels than larger vessels. The parameter on the coefficient of variation was positive suggesting risk seeking behaviour, similar to that observed in other studies (Holland and Sutinen 2000).

The model estimated effort allocation was compared with the actual effort allocation observed in 2008 (Figure 4.9). Correlation between actual and estimated effort allocation was reasonably high (r=0.73), although the model tended to overestimate effort in the northern zone, and underestimate effort in the central zone.

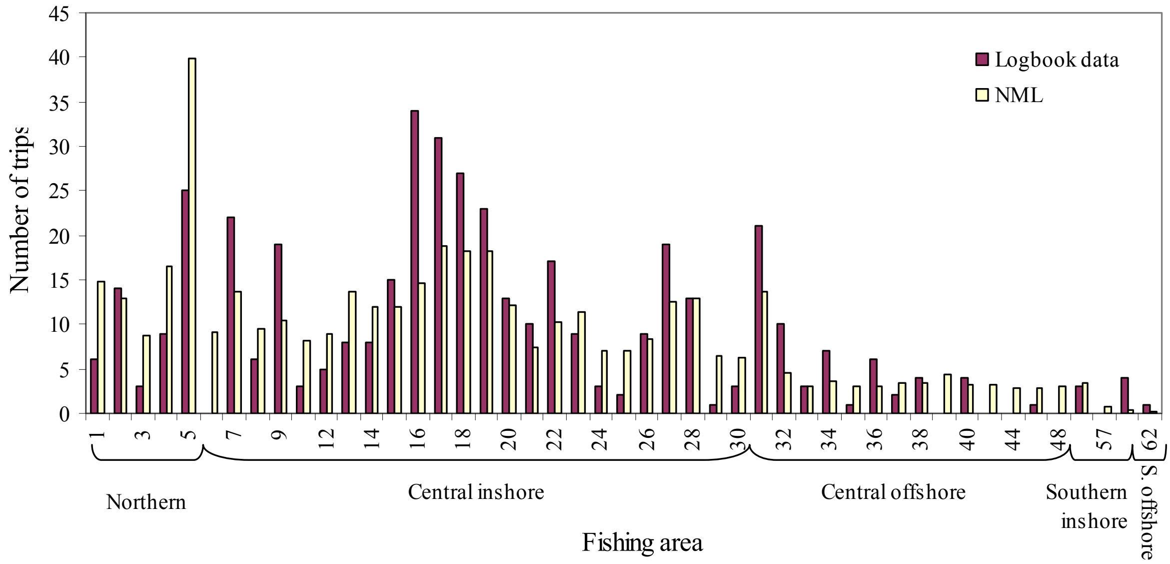

Figure 4.9. Actual and estimated distribution of fishing days, 2008

Overall, the NL model provides a reasonable estimate of the allocation of fishing effort over the period of the data examined. While the McFadden Pseudo R^2 (McFadden 1974) was low, this was generally consistent with reported statistics in other studies of fisher location choice (Holland and Sutinen 1999; Smith 2002; Marchal *et al.* 2009). Similarly, the correlation between actual and estimated effort allocation was equivalent, if not higher, than observed in other studies (Hutton *et al.* 2004).

<u>The north and south ports model</u>

The analysis was extended to include the Cairns fleet in the north, and also the Sydney and Ulladulla fleets in the south. Given the substantial difference between the fishing pattern of the

[11] This is also borne out in the relatively small impact of VPH the previous year on the expected utility of fishing in a given location compared with the VPH the previous week (Table 3).

different fleets, two separate location choice models were estimated – one for Cairns and Mooloolaba and the other for Sydney and Ulladulla. The variables used were the same as those used for the preliminary analysis.

The estimated coefficients for the two models are given in Table 3.9. As can be seen, the parameter estimates for the combined Cairns/Mooloolaba model are generally similar to the Mooloolaba model only, but the model parameters for the southern ports are substantially different.

Table 3.9. Estimated NL model parameters for the extended analysis

	Northern Vessels				Southern Vessels			
Variable	Coeff	St. error	Coeff/ St.Er.	P[Z>z]	Coeff	St. error	Coeff/ St.Er.	P[Z>z]
Utility model								
VPH Week-1	0.138	0.004	31.076	***	0.087	0.007	12.531	***
VPH Year-1	0.025	0.003	7.521	***	0.011	0.009	1.270	
Density Week-1	0.169	0.005	34.17	***	0.280	0.014	19.438	***
Density Year-1	0.029	0.006	4.993	***	0.091	0.017	5.526	***
Coeff. Variation	0.991	0.047	21.141	***	0.433	0.102	4.247	***
P*distance	0.019	0.001	21.801	***	0.006	0.001	6.049	***
P*distance/days	-0.004	0.001	-6.735	***	-0.002	0.000	-3.737	***
P*distance/length	-0.359	0.016	-21.79	***	-0.128	0.020	-6.324	***
Inclusive values								
North	1.000							
Central inshore	0.955	0.010	91.27	***	1.000			
Central offshore	0.903	0.012	73.602	***	0.899	0.055	16.206	***
South inshore	0.587	0.022	27.165	***	0.989	0.026	37.648	***
South offshore	0.554	0.081	6.876	***	0.899	0.055	16.206	***
Underlying standard errors								
North	1.283							
Central inshore	1.343	0.015	91.27	***	1.283			
Central offshore	1.420	0.019	73.602	***	1.427	0.088	16.206	***
South inshore	2.186	0.080	27.165	***	1.296	0.034	37.648	***
South offshore	2.314	0.337	6.876	***	1.427	0.088	16.206	***
Model diagnostics								
Chi squared		19723.6				4700.8		
Log likelihood		-24271.5				-6410.9		
McFadden Pseudo R-squared		0.289				0.268		
AIC		6.458				5.956		

*** significant at 1% level; ** significant at 5% level, * significant at 10% level

None of the vessels in the data set from the southern ports fished in the northern zone, so this was excluded from the analysis. Further, the central and southern offshore zones were also merged together (i.e. forced to be the same) for the final analysis as there was no significant difference between them in earlier estimations and the combined model performed better than the model with the zones separate.

From Table 3.9, the southern boats appeared less responsive to VPUE than the northern boats, more responsive to the density of vessels and less risk-seeking (i.e. lower coefficient on the coefficient of variation suggesting that they follow the pack more than being risk seekers).[12]

4.3.3 Simulation model

Using parameters estimated in the RUM a simulation model was developed which could predict fishing locations and profits, given spatial incentives or closures. The simulation model used the set of observed trip level data for 2004 and 2007 for each of the ports examined. The probability that a given trip would be applied to a particular area was estimated using equations 1-4 above, based on the trip specific information and the coefficients of the RUM given in Table 3.9. The total effort by port in each area was determined by summing the probabilities across all trips from that port.

To simulate the effects of the hook decrementation system, the VPUE was reduced accordingly. This had the effect of reducing the utility of fishing in the area and hence the probability that effort would be deployed there. For closures, the utility associated with a cell was forced to zero, so that the probability distribution was effectively estimated based on the set of available cells only.

The average vessel costs and revenues were also included into the simulation model in order to derive an estimate of the total profitability change for the fishery and by port. There were obtained from the recent ABARE report on the effects of the buyback program on the fishery (Vieira *et al.* 2010). An assumption was made that vessels on average had a similar cost structure in each of the ports.

The revenue at the trip level was estimated by multiplying the expected VPH for the week (the observed VPH in each cell multiplied by the probability that the vessel would fish in that cell) by the number of hooks and the number of shots that trip. This was summed over ports and also the fishery as a whole, and estimated for the benchmark scenario (no change) as well as the simulated scenario. Change in average vessel revenues at the fleet and port level were estimated by multiplying the average observed revenue from the ABARE report by the estimated percentage change in revenue from the model.

Similarly, changes in fuel costs were based on the percentage change in the total distance travelled multiplied by the average fuel costs from the ABARE report. Change in crew costs were estimated as percentage of the change in revenue (as crew are paid a proportion of the revenue). Change in average profits was then estimated as change in revenue less change in fuel costs and crew costs. All other costs were assumed to remain the same.

[12] The estimated parameter values are guides only to the responsiveness as the marginal effect of a change in these parameters needs to be determined to estimate the actual responsiveness.

5. Results

The models were applied to a number of scenarios involving different areas of the fishery subjected to either a full closure or different levels of hook penalty. The two models operate in fundamentally different ways, each with advantages and disadvantages. Similarities and/or differences in outcomes under each scenario for the two models provide an indicator of the degree to which the results can be considered representative of the likely outcomes under each scenario.

In this section, the models are briefly described again in the context of their use in the scenario analysis. The scenarios themselves are also described. These are hypothetical scenarios in order to examine the efficacy of the hook decrementation system as well as test the effects of model assumptions on the results, but have some link to a potential management response. The results of each model are presented, followed by a discussion on the similarities and differences between model results, and the implications for closures versus hook decrementation systems.

5.1 General recap of the key model features

The models used in the study have been described in detail in the previous section of the report. A brief overview of the models is again presented in order to set the scene for the scenario analysis.

5.1.1. The random utility model

The RUM is a statistical model that effectively determines the probability that effort will be applied to a particular area given its characteristics. In essence, effort is spread across the fishery based on its probability, with effort concentrating in areas that have a higher probability. The approach assumes that fishers aim to maximise their utility, and the level of effort applied to a particular area reflects the utility derived from that area. Hence, the analysis is based on revealed (observed) preferences. Given that we can observe the characteristics of the area, the contribution of these characteristics to the expected utility can be derived.

The key driver in the model that is affected by a hook decrementation program is the expected effective value per hook deployed. As the model is based on expectations (as presumably the actual outcome cannot be known until effort is deployed in an area, following the decision to fish there), this is represented in the model by the value per hook in the previous week. Given fishers are faced with a choice of areas and a limit on the total number of hooks that can be deployed over the year, then fishing in an area with a hook penalty reduces the expected value per hook consumed in that area.

For the purposes of estimating the outcomes under a particular scenario, a simulation model was constructed around the RUM. The simulation model was used to estimate the distribution of fishing effort as a result of either reducing the expected value per hook (i.e. the value in the previous week) in the scenario areas, or preventing fishing entirely in these areas (i.e. a closure). The actual average observed value per hook in each area was applied to the resultant effort distribution and the change in revenue as a result of this effort re-distribution was estimated. Similarly, changes in fuel costs were estimated by the overall change in distance travelled. From these, the impacts on average fleet profitability (by port and total fleet) could be estimated.

The RUM model includes vessels from four ports: Cairns, Mooloolabah, Sydney and Ulladulla. These ports capture the bulk of the fishing activity across the fishery. As each vessel (and indeed each trip) is identified separately in the analysis, estimates of change in profitability by vessel is also possible in the model analysis.

5.1.2 The dynamic State Variable Model

Dynamic state variable modelling (DSVM), a form of dynamic programming, has its basis in the ecological and economic literature (Clark and Mangel, 2000; Mangel and Clark, 1988). It is a discrete-time dynamic optimisation method used to model a state-dependent decision over time, where each decision is made by maximising expected future rewards (Babcock and Pikitch 2000). This allows decisions influenced by qualitatively different, and possibly unrelated factors to be based on the value of a single currency. Factors such as the availability and value of different fish species, quotas, costs of travel and risk to fishing vessels influence decisions as they affect the final value of the landed catch (Gillis et al 2005). The decision-maker's "state" includes any information about its condition that can influence the expected reward from each option. For fishers choosing strategies to maximise utility (usually defined as profit), the state could include the catch of various species in the hold (Babcock and Pikitch, 2000, Gillis et al. 2005) or the amount of trips or quota remaining (Gillis et al. 2005, Poos et al 2010, Dowling et al in prep). DSVM also allows short term choices to be reconciled against long time constraints, as in the case where fishers face an annual quota but make daily decisions about fishing location, targeting and/or discarding (Poos et al. 2010). A dynamic state variable model calculates state-dependent decisions over time, by treating the state space as a discrete number of cells, across which the dynamics programming equation calculates the maximum expected profit and the optimal choice at each time across all states. The model is backward-iterative, since the optimal choice in each time period depends on the expected returns in the future.

The dynamic state variable model used here is that described in Chapter 4, a model for state dependent behaviour of various fishing vessel types, translated into behaviour of the fleet and implemented using stochastic dynamic modelling (Mangel and Clark 1988; Clark and Mangel 2000). The model describes a multi-species fishery with moving stocks of varying seasonal availability, and alternative targeting strategies which yield differing catch compositions.

We assume 3 vessel types of increasing capacity defined by the vessel's maximum speed, travel costs, cost per shot, and the maximum time the vessel can remain at sea (largely influenced by the storage volume and/or freezing capacity of the hold), which in turn confers a maximum number of longline sets, or "shots", per vessel during a trip. The modelled vessels operate out of two ports (nominally Mooloolaba and Sydney). Consistent with the operations of longline vessels (Campbell 2007), we assume that one shot equates to one day of the season, so that laying x shots requires x days. Since days will be lost due to weather conditions and social demands, there is an overall upper limit on the number of shots per fishing season.

We parameterized the model using set-by-set longline data obtained from the databases held by the Australian Fisheries Management Authority (AFMA). In particular, we inferred patterns of quarterly fish movement and relative availability by standardization of catch-per-unit-effort (CPUE) data, and we inferred targeting strategies by performing cluster analyses on the catch composition of the sets reported in the logbooks. In order to make the model tractable, we used a simplified representation of the ETBF, with fishers operating out of two ports, and fishing in one of 24 5-degree regions. We include only the main three target species of yellowfin tuna, albacore tuna and broadbill swordfish, although the fishery has also targeted bigeye tuna and striped marlin. The specific details of the fishery and vessel parameterisation may be found in Chapter 2.

The state variable in our model is the effort (number of shots) remaining at time t in the season for a vessel. We assume a fishing season of length 120 days. We assume a constant underlying stock size, N, through time, implying fishing does not affect local abundance. This is consistent with the hypothesis that for large pelagics, which are highly migratory (Brill et al. 2005), local replenishment occurs.

Vessels may only travel to one 5 degree-square location per trip, which is consistent with general observed fleet behaviour (Pascoe et al 2010). In addition to choosing a fishing location, a vessel may remain in port at any given time. As such, there are effectively 25 "location" states (the 24 at-sea regions and the state of remaining in port), and ((24 x $Ntarg$) + 1) state spaces, where $Ntarg$ is the number of targeting strategies. If a vessel remains in port, it is assumed to do so for one day, so that t is incremented by 1, after which the decision of where to go fish is made again. Staying in port allows a vessel to get "in phase" with the oscillating catchability or "out of phase" with supply in the market, and thus avoids the expenditure of capital when catchability and/or price is low.

For each species, species-specific price was determined endogenously by treating price dynamics as a game (Clark and Mangel 2000). A forward-and-backward (FAB) approach was used, assuming that price is a function of the species-specific volume $V_t(s)$ of landings by all vessels each time step. This generates a new species-specific price trajectory as a function of time, $p(t,s)$, as the simulated vessels return to port with their catches: $p(t,s) = p(\mathrm{V}(t,s))$. We stabilized the dynamic game (Houston and McNamara 1999, Clark and Mangel 2000) by the method of errors in decision making.

For consistency with the Random Utility Model to the extent possible, the total effort quota was scaled according to the total number of trips that had originated out of each port in the year of interest. Given that the state space increases significantly with the additional of ports, the modelled Sydney port was assumed to be a proxy for all vessels operating from this port and all ports to the south of Sydney. The effort quota was set to 100 sets for the Mooloolaba-based vessel types, and the effort quota allocated to vessel types operating from "Sydney" port was the fraction of 100 sets corresponding to the relative proportion of trips originating from Sydney, Ulladulla and all other southern ports. For the 2004 scenarios this was 70 (2409 trips originating from Mooloolaba; 1677 from and south of Sydney), and for the 2007 scenarios this was 53 (1709 trips originating from Mooloolaba; 907 from and south of Sydney).

5.2 Scenarios examined

Fishery interactions with threatened and protected (TEP) species, such as the incidental catch of albatross, flesh-footed shearwaters and turtles, are of concern in the Eastern Tuna and Billfish Fishery. Although there is a threat abatement plan for seabirds under the EPBC act that has involved catch rate limits, area closures and mitigation measures for seabird species, these are mandated independently of measures or turtles and other TEP species. The variety of measures for addressing various environmental issues, such as trip limits for sharks, operational modifications for reducing turtle catch, and voluntary avoidance of some billfish species has meant that the fishery is not taking an integrated approach to the management of target and TEP species. An alternative approach, under a catch or effort quota system such as that detailed in the 2005 management plan, could use spatial incentives as a management tool to avoid TEP by-catch with minimal direct constraints on how fishers choose to operate. By using SAFs (spatial area factors, as per the 2005 management plan) to create disincentives to fish in particular areas when there is a high probability of encountering TEP species, these existing incentive measures could be used as a cost efficient alternative to the current spatial management policy of marine reserves and fishery closures.

In the scenarios presented in this chapter, we assume that the fishery is managed via a total allowable effort (TAE) quota, as was to have been in the process of implementation at the commencement of the project. We acknowledge that the fishery is now moving to a catch quota system, and discuss the efficacy of adapting the respective modelling approaches to evaluate incentives in this context in the next chapter Under the assumed TAE system, the hook decrement incentive system is implemented by assigning SAFs to each fishing location. These SAFs can vary over the course of the fishing season. Here we examine a set of scenarios in which the goal is to design an incentive map that minimizes capture of threatened species with minimal loss of access to target species.

We consider 20 scenarios involving i) varying levels of hook decrement (3); ii) varying locations for application of the incentive (3); and iii) alternative years in which the measure is applied (2) (3 x 3 x 2 = 18); plus "baseline" scenarios of no "management change" for each of the two years considered (Table 4.1). Identical scenarios are considered for different years since fish distribution, availability and targeting practices show strong differences between years, such that different years may almost be considered alternative “fishery regimes”.

Table 4.1 Summary of spatial incentive scenarios

Scenario	Year	Location	Hook decrement
Baseline 2004	2004	N/A	N/A
	2004	Mooloolaba	3:2 (1.66)
	2004	Sydney	3:2 (1.66)
	2004	South of Sydney	3:2 (1.66)
	2004	Mooloolaba	3:1 (3.00)
	2004	Sydney	3:1 (3.00)
	2004	South of Sydney	3:1 (3.00)
	2004	Mooloolaba	closure
	2004	Sydney	closure
	2004	South of Sydney	closure
Baseline 2007	2007	N/A	N/A
	2007	Mooloolaba	3:2 (1.66
	2007	Sydney	3:2 (1.66
	2007	South of Sydney	3:2 (1.66
	2007	Mooloolaba	3:1 (3.00)
	2007	Sydney	3:1 (3.00)
	2007	South of Sydney	3:1 (3.00)
	2007	Mooloolaba	closure
	2007	Sydney	closure
	2007	South of Sydney	closure

The spatial management unit, that is, the spatial scale at which incentives could be applied, was limited to the 5-degree spatial resolution of the dynamic state variable model (Figure 5.1) The random utility model had a 1-degree spatial resolution, but for sake of direct comparison, management was applied at the coarser scale of the two models.

Statistical models of albatross distribution (Wilcox, unpublished data) based on historical encounter rates, predicted that the highest encounter rates occurred in the 5-degree spatial zone immediately to the south of that encompassing Sydney and closest to the coast, while the second-highest encounter rates were within the 5-degree coastal square encompassing Sydney (Figure 5.1). This area has been the focus of management activity to reduce seabird bycatch in recent years. The Australian Fisheries Management Authority (AFMA) has imposed closures to daytime fishing within the 5 degree square encompassing Sydney in attempts to minimise seabird encounters. As such, we explored spatial incentives in each of these two regions. We also explored incentives in a third region, the 5-degree area immediately offshore from Brisbane/Mooloolaba (Figure 5.1). This region was selected as interactions with marine turtles are an emerging issue in the fishery, and the area off of southeastern Queensland is a potential target for management due to the high concentration of turtle nesting sites in the region.

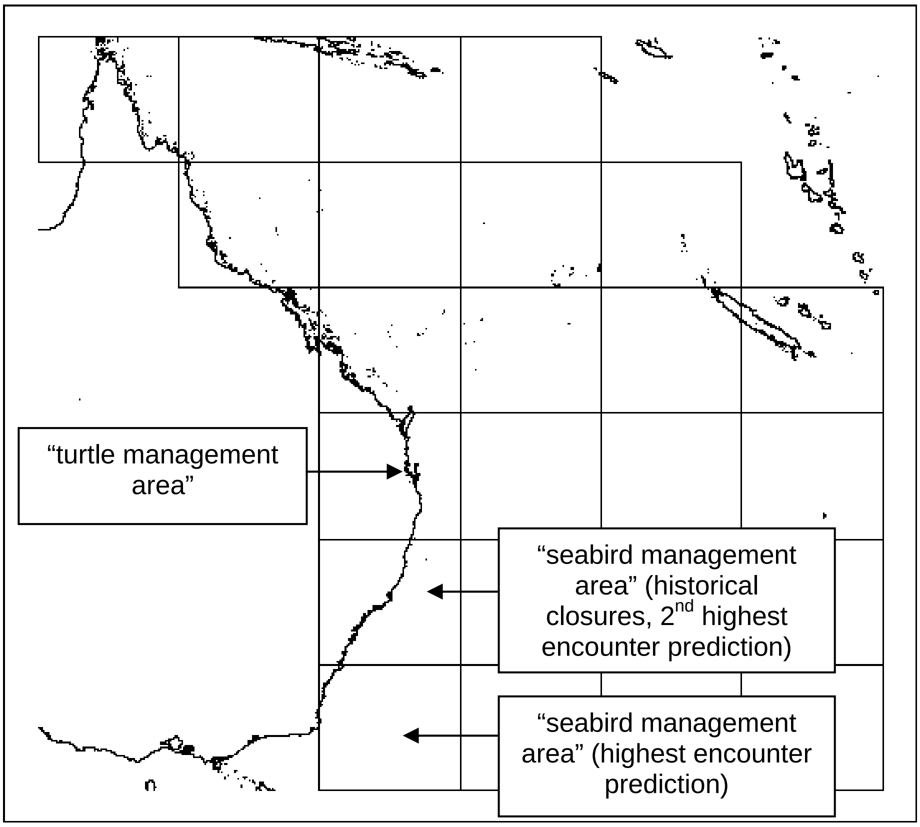

Figure 5.1 Map showing the 5-degree spatial delineations used in the dynamic state variable model, and indicating the three areas to which modelled hook decrement incentives and closures are applied.

Two levels of SAFs were considered in addition to spatial closure scenarios (SAFs in the context of the DSVM are implemented at the shot level, instead of as individual hooks as fisher's quota is expressed in shots in the model). The first was 3:2; that is, for every 2 units of effort (shots) applied in the area of spatial management, 3 units (shots) were decremented from the quota. The second was 3:1; for every unit of effort applied in the area of spatial management, 3 units of effort were decremented from the quota. It was intended that these would approximate moderate and strong spatial incentives, respectively.

Annual spatial maps of catch composition (Campbell 2008) suggested that the years 1997, 2003 and 2007 embraced the main targeting practices (set types and catch compositions) historically known to have occurred in the fishery. In 1997, the fleet was mostly inshore, with swordfish and yellowfin tuna comprising the majority of the catch. Offshore expansion peaked in 2003 as a result of inshore depletion of swordfish, with the majority of the catch being yellowfin, swordfish and albacore. The introduction of swordfish total allowable catches in 2006, together with increasing fuel prices, resulted in Mooloolaba-based vessels shifting onto lower-value, but highly abundant, albacore in more northern latitudes. The targeting of albacore in these regions also resulted in coincidental catches of higher-value yellowfin that exceeded inshore catch volumes of this species at this time. Export markets were successfully sought for albacore, resulting in the ongoing active targeting of this species. The data informing the Random Utility Model commenced in 2003, but due to the need to have a year lag in the model, the earliest year that could be considered was 2004. As such, two years of the fishery were considered here: 2004 and 2007.

5.3 Results

5.3.1 Effort reductions in the management areas

The change in effort in the area to which the management instrument was applied was estimated under both 2004 and 2007 conditions. A baseline run of both models was undertaken with no management intervention, and this was compared to the results from runs with management restrictions. Two levels of hook penalties were applied to each management area – a 3:2 penalty (where 3 units of hook quota were consumed for every 2 hooks deployed) and a 3:1 penalty (where 3 units of hook quota were consumed for every hook deployed). A total closure of the area was also imposed for comparison.

As would be expected, the closure of the area resulted in a 100% reduction in effort in the closure area for all model runs as perfect compliance was assumed (Figure 5.2), the exception being in the DSVM model which had a baseline effort level of zero in the area off Brisbane in 2007 (hence effort could not decrease further).

In both models, the introduction of a hook penalty resulted in a reduction in fishing effort in the management area, and the magnitude of this reduction generally increased with the increasing hook penalty (Figure 5.2). The DSVM model was more sensitive than the RUM model in terms of response to the hook penalty, with greater reductions being observed in all scenarios. The DSVM model attaches a higher cost to the use of a hook at any point in time as it has an opportunity cost in terms of its foregone future use. The RUM, in comparison, is myopic as it treats all trips independently, and only considers the relative benefits of fishing in each area in one point in time.

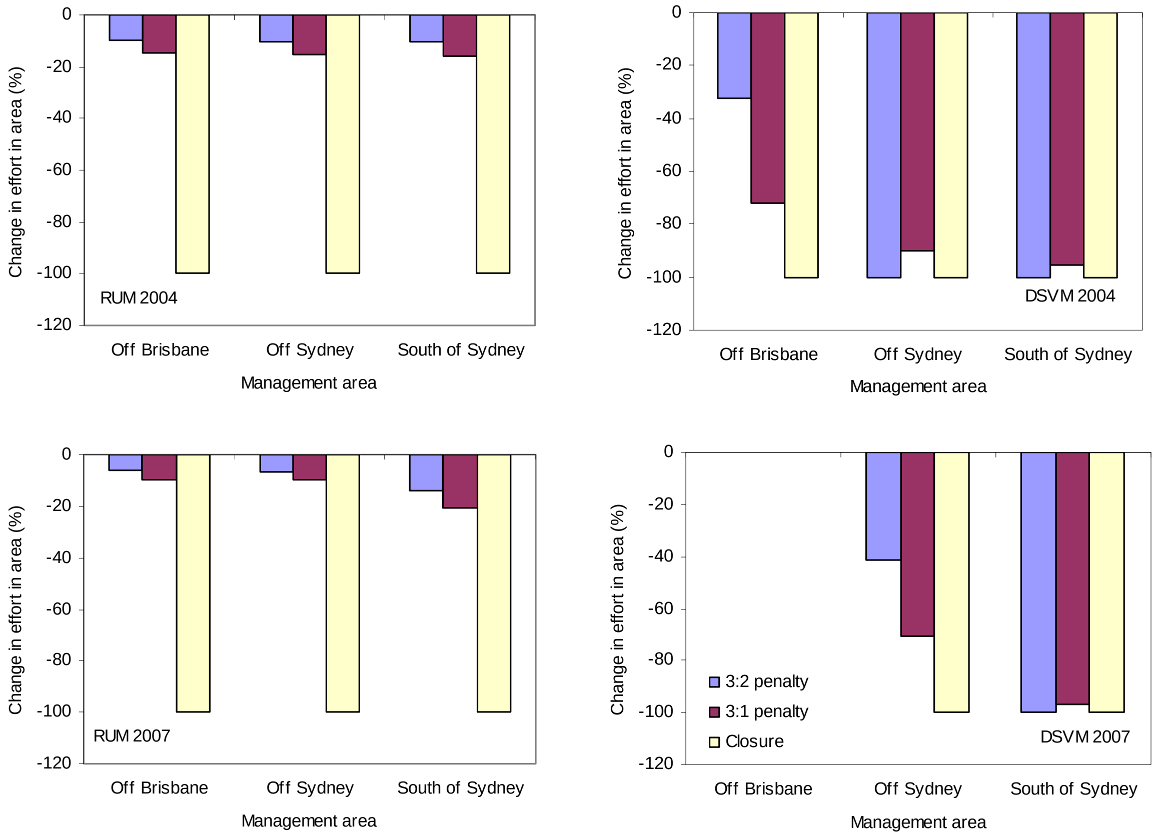

Figure 5.2 Estimated changes in fishing effort in the management areas examined

An unusual outcome of the DSVM was that, in some cases, the higher hook penalty resulted in a marginally (i.e. 4-5 percentage points) lower effort decrease in the management area. Given that the DSVM optimises fishing activity over time and space, and given the highly non-linear nature of many of the model parameters, this discrepancy may just be an artefact of the model, and reflect difficulties in solving models involving time and relative dimensions in space.

5.3.2 Changes in catch composition

The DSVM includes information on catch composition arising from the spatial and temporal effort allocation. This information is not included in the RUM model directly, although differences in catch composition (as well as abundance) are reflected in the relative expected value per hook in each area which includes all species caught in a location, their abundance, and their average price.

The estimated baseline spatial catch composition of the three key species (yellow fin tuna, albacore and broadbill swordfish) is shown in Figure 5.3 for each of the two years of the analysis. The model results suggest that an optimal strategy for the fishery would have been to have fished more offshore in 2004, targeting mainly swordfish, and moving more inshore and to the north in 2007 targeting albacore in the north and yellow fin tuna in the south.

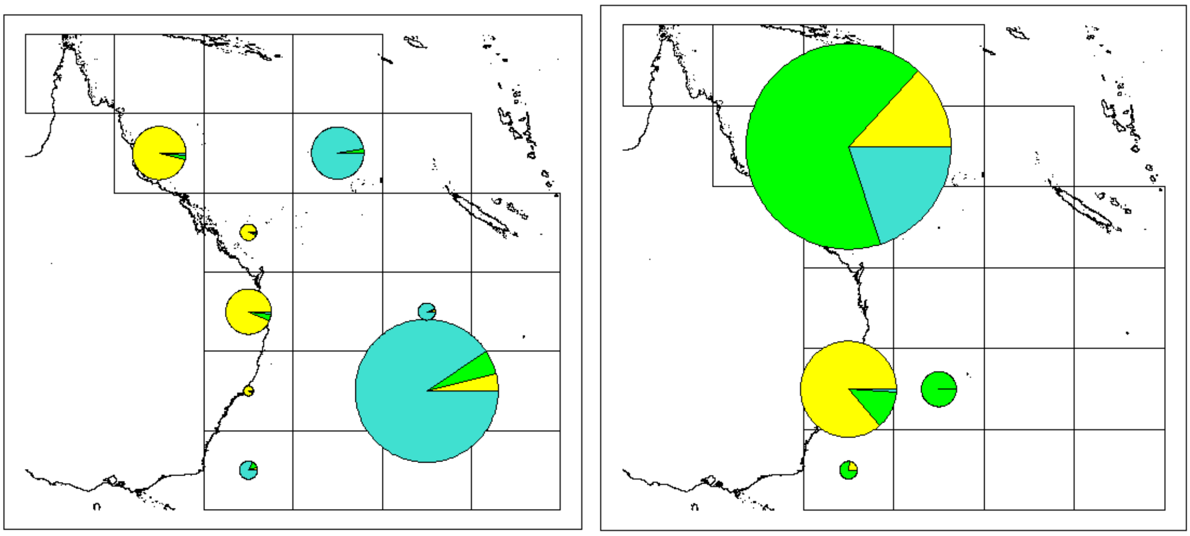

Figure 5.3 Baseline catch composition for a) 2004 and b) 2007 from the DSVM (yellow=yellow fin; green=albacore; blue=swordfish, marker diameter indicates total catch volume)

The impacts of the different management actions on the optimal spatial catch distributions are shown in Figures 3.4 and 3.5. In most cases, the general catch composition does not change substantially as a result of the different management actions, but the location of their catch does. These effects vary also by year, reflecting differences in the average value per hook in different areas which is driven by relative stock abundance and distribution in that year. For example, increasing the hook penalty in the area off Brisbane given the 2004 stock conditions results in the same catch being taken further north, while under 2007 conditions, there is no change.

A change in catch composition as well as catch location was estimated to be optimal under 2007 stock conditions when management actions were applied to the areas off Sydney and south of Sydney. In both cases, catches of albacore was estimated to increase, with inshore catches of yellow fin decreasing (Figure 5.5).

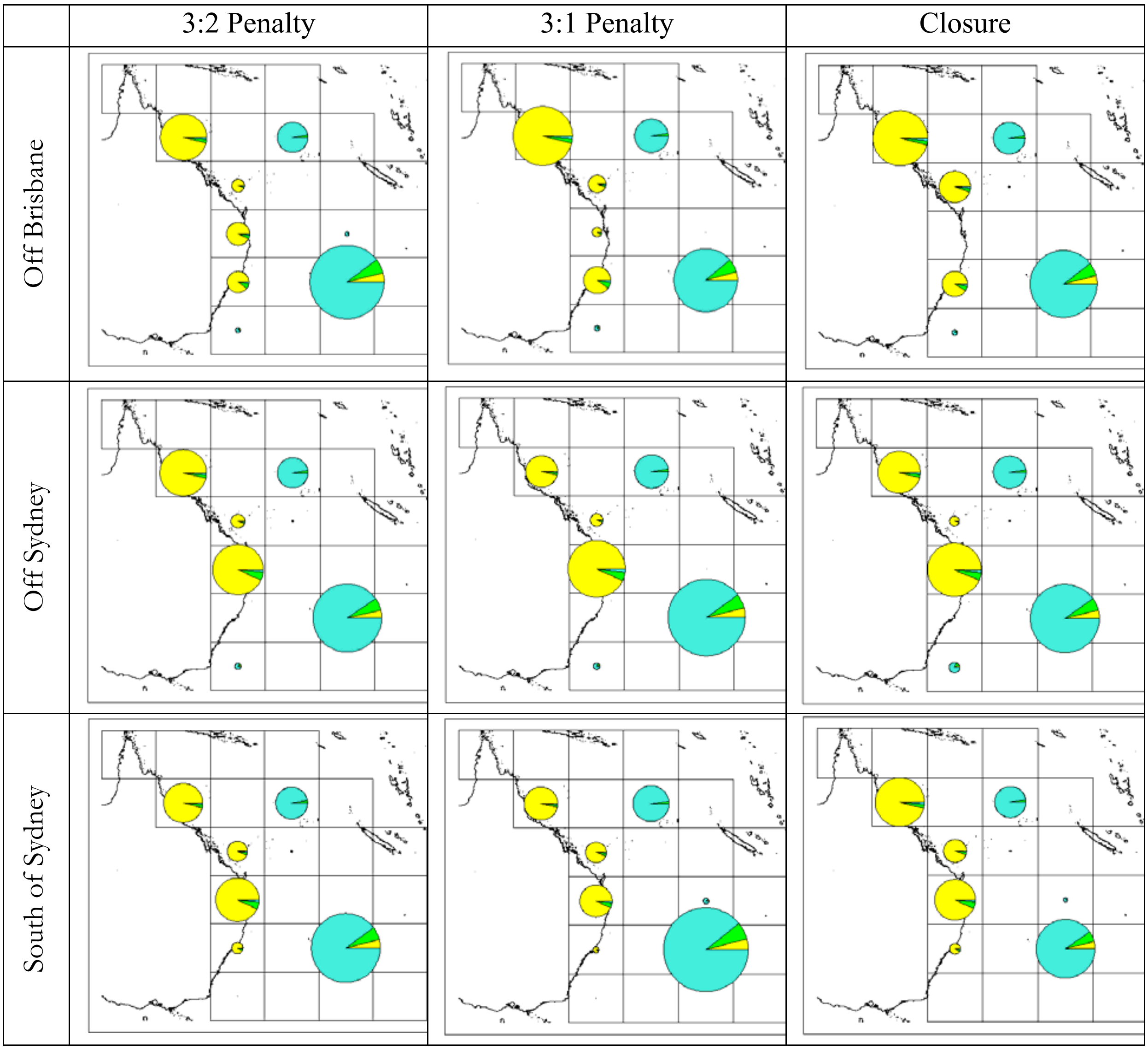

Figure 5.4 Spatial catch distribution under the different management options and 2004 stock conditions from the DSVM (yellow=yellow fin; green=albacore; blue=swordfish, marker diameter indicates total catch volume).

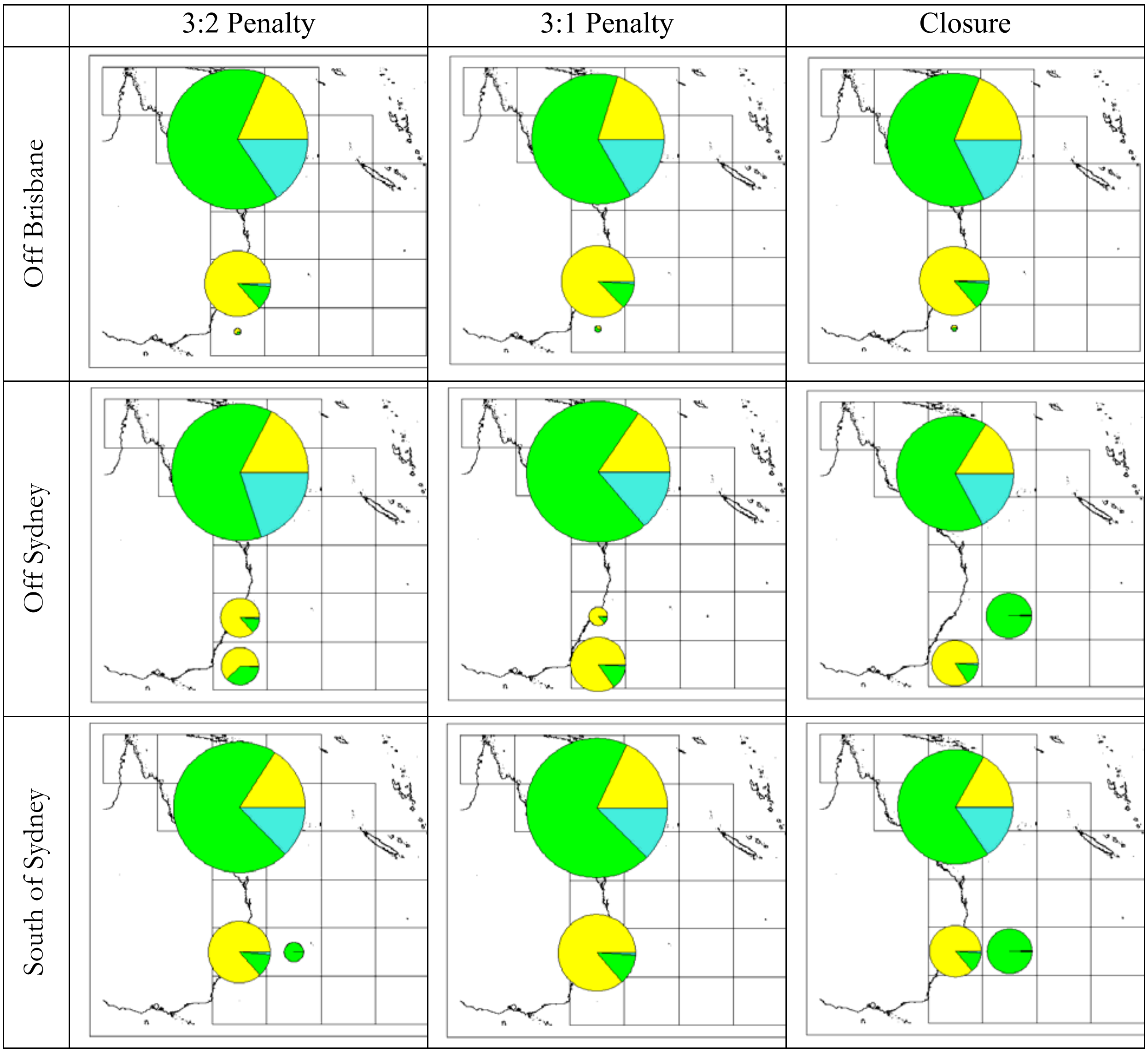

Figure 5.5 Spatial catch distribution under the different management options and 2007 stock conditions from the DSVM (yellow=yellow fin; green=albacore; blue=swordfish, marker diameter indicates total catch volume).

5.3.3 Changes in profitability

The model estimates of change in fleet profitability varied considerably (Figure 5.6). In all simulations, however, a closure off Brisbane resulted in an increase in total fleet profitability.[13] This was largely driven by cost savings from the more southerly vessels not travelling to these areas. In other scenarios, the RUM predicted a net reduction in profitability at the fleet level, although the DSVM suggested that profits may increase with a 3:2 hook penalty, and also with a closure.

[13] In contrast, the initial RUM analysis for the Mooloolaba fleet on its own suggested that a closure off Brisbane would result in a greater loss in fleet profits than a hook decrementation system (Pascoe *et al.* 2010). The earlier analysis used 2008 data as the benchmark, suggesting that the outcomes may vary considerably by year

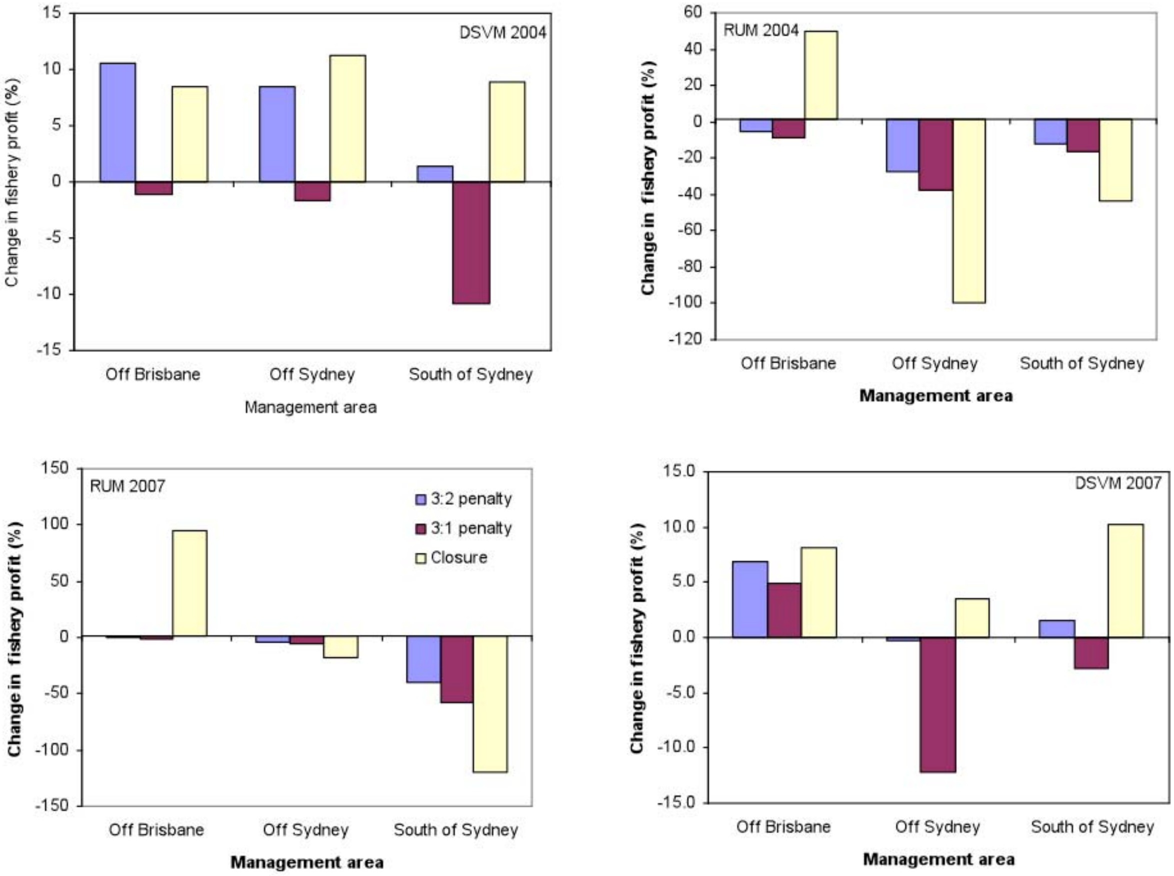

Figure 5.6. Relative change in fleet profitability from the different models and scenarios

For the random utility model, changes at the individual port level suggest that distributional consequences of the different options are considerable (Figure 5.7). The southern port of Ulladulla appears particularly vulnerable to any management measure imposed in the areas off Sydney or south of Sydney. Under 2004 conditions, the vessels in the port would have been economically unviable[14] under any scenario in these areas, while vessels in Sydney would also have been economically unviable if the area off Sydney had been closed. Under 2007 conditions, vessels in Ulladulla would, again, be economically unviable under any of the modelled management options if applied in the area south of Sydney, and would be economically unviable if the area off Sydney was closed.

At the other end of the extreme, vessels from Cairns were largely unaffected by any of the management scenarios examined. Where a change was observed, this was usually small (less than 2% in most cases) and positive. Larger positive changes in profit were observed for the Cairns boats with a closure off Brisbane, with fishing effort expended in this area being diverted to nearer fishing locations.

[14] That is, the reduction in average profits of vessels in the port decreased by greater than 100%.

Using the DSVM, port-specific results (Figure 5.8) also suggested, at least for 2004, that the "Sydney" port (being a proxy for Sydney and Ulladulla) was more vulnerable to management measures than the Mooloolaba port, but relative changes in profit were of a much lower magnitude than for the RUM (Figure 5.7) and indeed may simply reflect the different price trajectory that resulted from the game played under altered conditions. Both ports experienced a (maximum 14%) increase in profit with closures in either year, in contrast to the RUM when this closure was off or south of Sydney. Generally, the 3:1 penalty affected the Sydney port more adversely than the Mooloolaba port, while the 3:2 penalty south of Sydney resulted in small losses for the Mooloolaba port and gains for the Sydney port in both years.

There was no consistent pattern in profitability by vessel type with management strategy or between years, as evaluated using the DSVM (Figure 5.9). The few consistencies included i) the increase in profit for the highest and lowest capacity vessels, and loss for the moderate capacity vessels, for any management measure applied off Brisbane in 2007, and ii) the increase in relative profit experienced by the moderate capacity vessel type under the 3:2 penalty or under a closure in 2004, irrespective of where the measure was applied. However, it should be noted that overall small changes in profit when considering the fleet as a whole, or by port, are here revealed to often be the result of larger losses experienced by some vessel types being offset by gains experienced by other vessel types. For example, for the 2004 scenarios, management measures imposed off Brisbane or south of Sydney resulted in profit increases for the highest capacity vessel types but losses for the moderate and sometimes low-capacity vessel types.

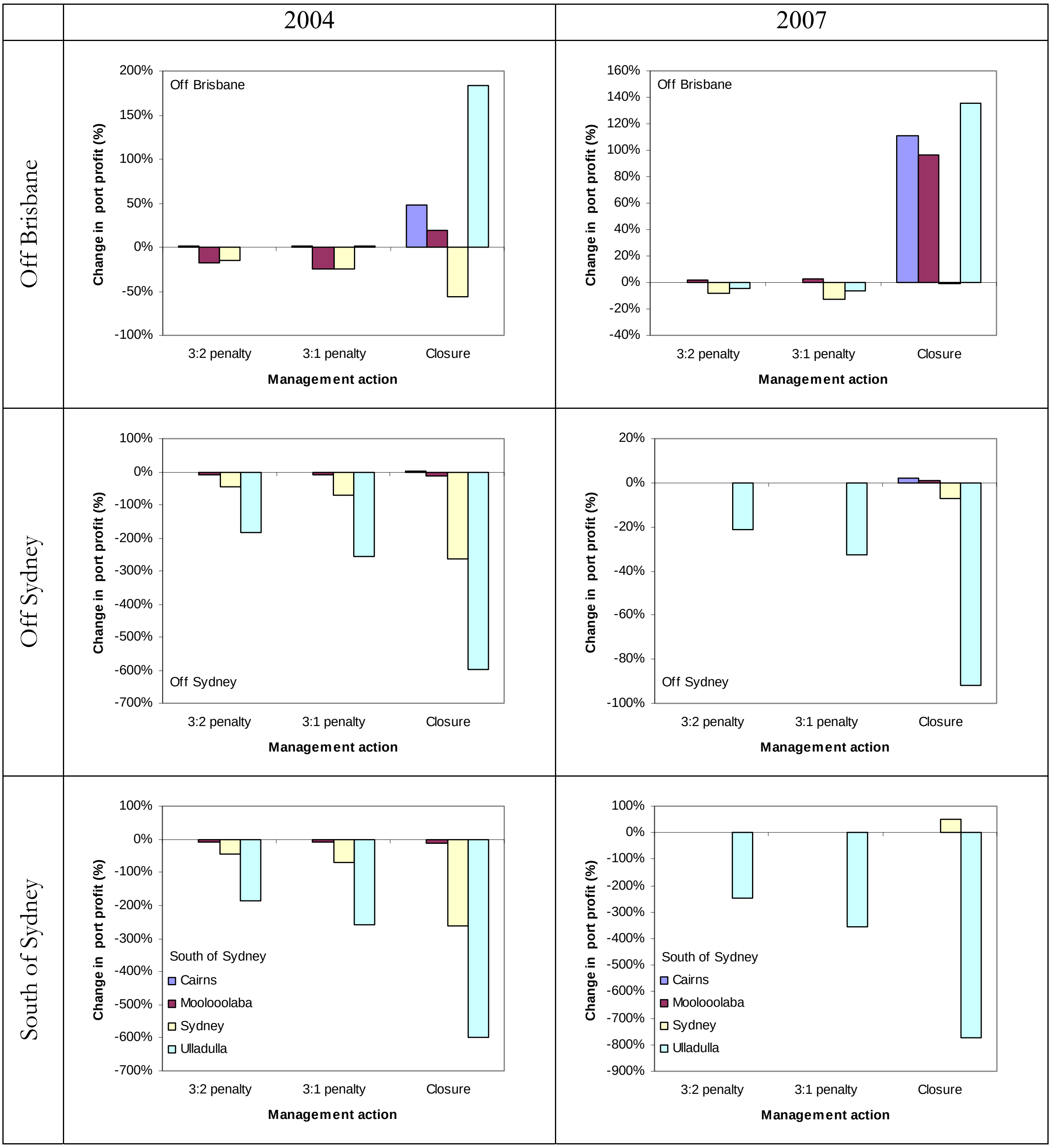

Figure 5.7. Relative change in average vessel profitability in each port using the RUM for different scenarios

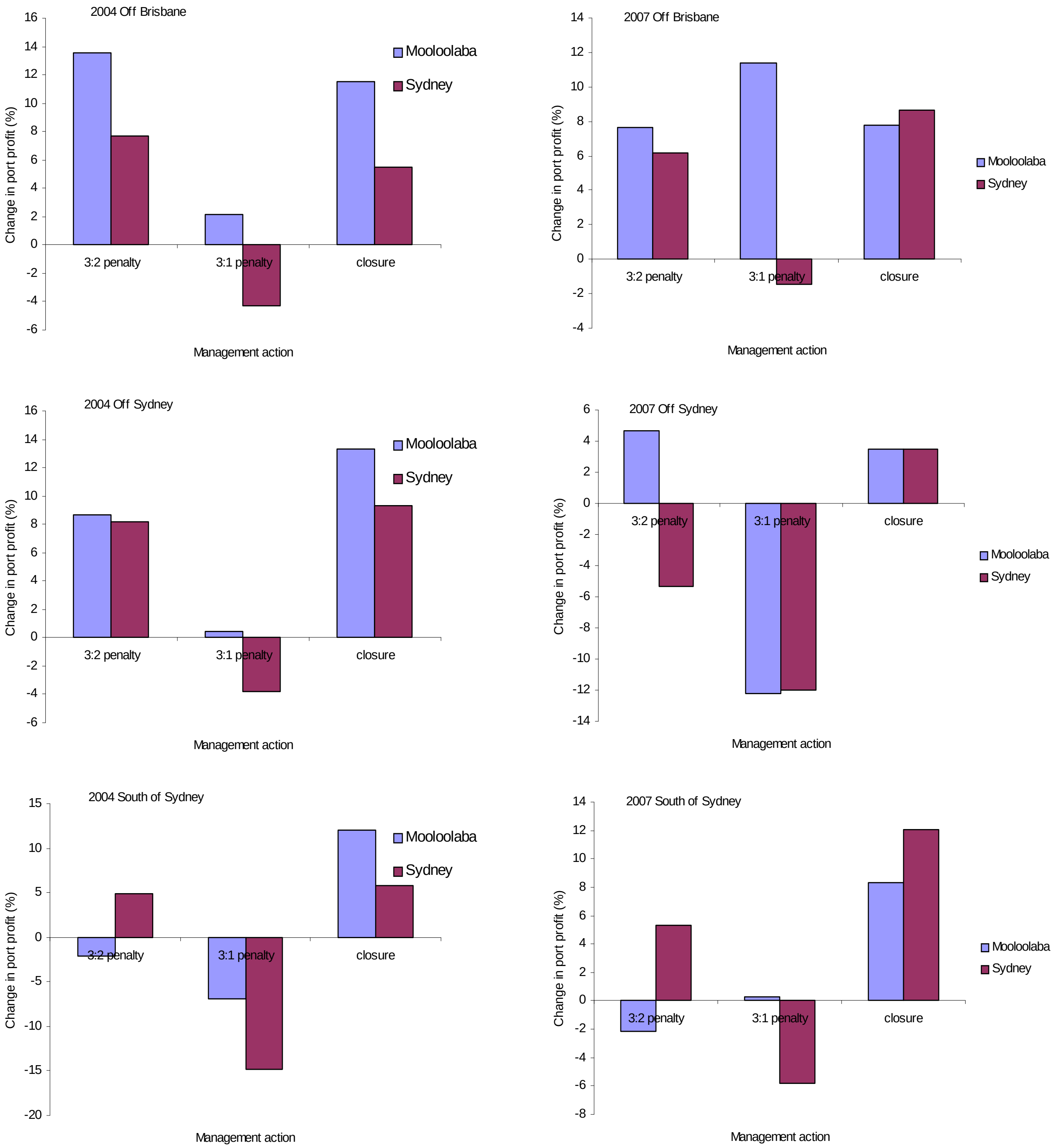

Figure 5.8 Relative change in average vessel profitability in each port using the DSVM for different scenarios

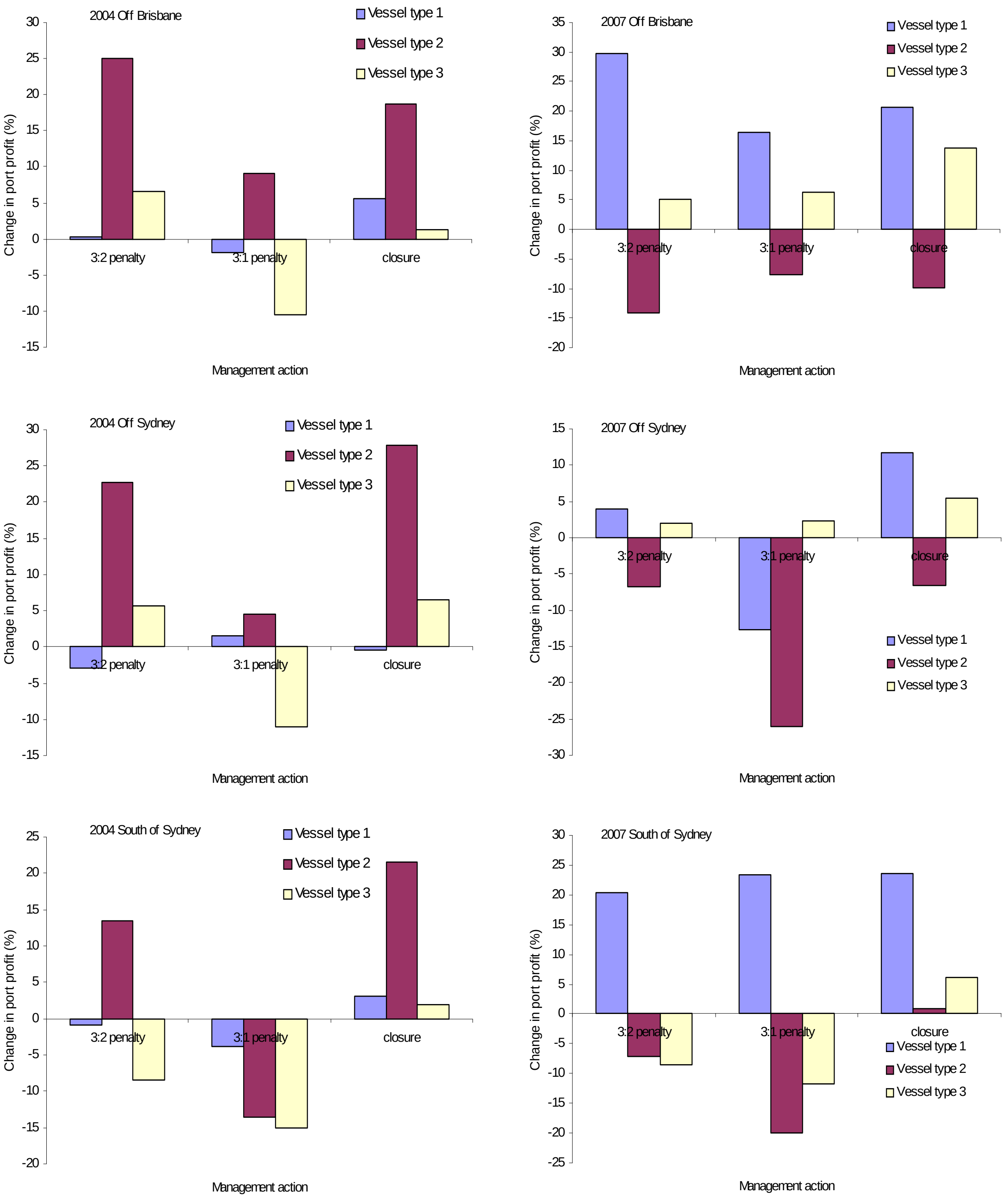

Figure 5.9 Relative change in average vessel profitability by vessel type using the DSVM for different scenarios

6 Discussion

6.1 Pros and Cons of each model

6.1.1 Dynamic state variable model

As it is currently formulated, the dynamic state variable model assumes that fishers have perfect information and are able to instantaneously adapt to new circumstances. This results in a highly responsive model where the spatial effort patterns reflect the optimal profit in terms of the assumed price model and cost structures. There is little noise associated with incorrect decision making, so that for each scenario, the relative changes in profit and costs are very near the true differences under optimal decision making. While it is clearly unrealistic to assume instantaneous and perfect adaptation to new circumstances, the advantage of this assumption is that the model can be considered to yield the equilibrium results for a given set of circumstances: presumably, fishers will learn about current conditions and will thus ultimately distribute effort in such a way as to maximise profit.

The greatest strength of the dynamic state variable modelling approach over a statistical modelling approach is its ability to acknowledge opportunity cost. The examples presented earlier illustrated that if operators are limited in how much they can fish, effort is utilized more effectively in terms of both when and where to fish, thereby maximising their overall profit level. This is evident in the overall smaller effects on profit predicted by the dynamic state variable model, in comparison with the random utility model. By considering future as well as immediate profit for a given level of remaining quota at a given time in the season, the dynamic state variable approach also more closely approximates the decision process of fishers: whether it is preferable to invest more immediately, or to delay until a more profitable opportunity arises. That is, decisions are made not just on spatial allocation of effort, but also when that effort is to be applied. This introduces the possibility of not fishing as being an optimal decision in some time periods, whereas this option would not be available in a statistical model based on pre-quota data. Unlike statistical models, where remaining in port is never optimal unless all other options involve negative profits, the possibility of not fishing being the optimal decision/location choice is a key means by which overall profit is optimized. This possibility of not fishing is further magnified by the consideration of market demand in determining price. By remaining in port, fishers can not only wait until fishing conditions and prices are higher, but can also influence the prices themselves to their advantage.

An additional advantage of the dynamic state variable modelling in the context of estimating fishery responses to new management regimes is that it does not depend on historical patterns for its predictive power (e.g. Bue et al 2008). This is in contrast to statistical models which assume myopic behaviour, where location choice is based on the set of current or expected conditions, and does not take into account potential future conditions, including the potential future use of quota. For example, if a fishing area is removed (representing a closure), the statistical models will only predict one outcome - a proportional increase in effort in the remaining areas (by each individual fisher). However, the distribution of effort may change radically, and not in a proportional manner with changes in the available areas for fishing (Costello and Polasky 2002).

In spite of these advantages, there are also significant drawbacks to the dynamic state variable approach as it is currently implemented. The first of these relates to the technical constraints of a large state space. As it is currently formulated, the model solves the dynamic programming equation via backward iteration for each of 120 time steps and each of 100 possible amounts of effort remaining at that time step, for each of 6 vessel type/port combinations, a total of 72000 solutions. For each combination of vessel type, port, time and effort remaining, there are 25 locations x 6 targeting strategies = 150 possible solutions. Increasing any one of the state variable or state space elements substantially increases the run time of the model and the difficult in stabilizing the dynamic price game.

As a result of these technical constraints, the model is overly simplified both in terms of its spatial resolution and its representation of vessel types and ports. A 5-degree spatial resolution is too coarse in an operational sense: the scale of fisher decisions, and indeed the oceanographic, biological and environmental effects that factor into decisions is on a finer scale. Moreover, spatial management becomes an increasingly blunt instrument at decreased resolution: the effectiveness of spatial incentives in protecting of TEP species without compromising access to target species will be difficult when implemented on such a large spatial scale. In addition, the simplification of the fleet to three vessel types and two ports is likely to be unrealistic, although this could be addressed by a better understanding via the data of the relative volumes of vessels of each capacity category operating out of each port. If this could be achieved, effort quota could be allocated among these in a more representative proportion, as opposed to equally. An associated issue is utility of developing better estimates of vessel capacity attributes and costs appropriate for each vessel type/port combination, but these are not currently accessible given the available data.

A more fundamental issue with the DSVM approach is that it is an optimisation, solving the dynamic programming equation to give the location and targeting strategy that yields the maximum profit for any state for all vessel and port types simultaneously. Put another way, all available effort is put to best use. As a result, the outcome set (the predicted spatial distribution of effort) is extreme and sparse. Although a small amount of error on location choice is introduced in order to stabilise the dynamic game, this is not of a magnitude to distort the optimal solution from being achieved on average. Thus the results do not show effort spread across more than, in these scenarios, one third of the possible areas (i.e. the maximum spatial extent of effort distribution was 8 of 24 spatial regions in the 2004 3:2 hook incentive applied off Mooloolaba. This is clearly not representative of the true spatial distribution of the fleet, although it may capture the main features. Thus it is somewhat problematic when it comes to evaluating the effect of spatial management, particularly when only a small amount of modelled effort occurs in the region of interest in the baseline scenario.

The issue of an extreme and sparse outcome set may be able to be partially resolved if the effect of vessel competition were included in the DSVM. Currently there is no consideration of the potential decrease in relative profitability with increasing vessel density within an area. This would make the most profitable areas less attractive above a given level of exploitation, and force vessels to consider sub-profitable areas. It is generally understood that fishers prefer to operate in areas not being exploited by a high volume of competitors, although some co-operation may occur leading to intermediate vessel densities. A future extension of the DSVM could consider the inclusion of density dependence as an additional state variable. However, this would most likely have to come at the expense of the dynamic price game, since the additional complexity of an additional state variable would compromise the convergence ability of this aspect of the model.

6.1.2 The RUM

The key advantage of the RUM is that it can be applied at a much finer scale than the DSVM. In this case, the model was applied to a 1 degree grid (c.f. a 5 degree grid with the DSVM), although areas of low activity were aggregated into larger areas. The RUM is also based directly on observed behaviour, with the focus on trying to infer the unknown drivers of this behaviour (as opposed to assuming the drivers and searching for the likely behaviour as in the DSVM). The model can be used to estimate where effort will be deployed at any point in time given the set of conditions prevailing at that time.

The RUM uses individual trip data for the estimation of the model parameters, while the simulation model built around the RUM also uses this same individual trip information for estimating effort allocation. This means that the full heterogeneity is captured in the analysis. As each trip is estimated separately, the results can be aggregated to a port level or higher with relative ease.

The RUM determines the probability that a fisher will choose a given location based on its characteristics. This probability, when combined with the total number of fishing days, provides a spread of effort across the fishery, concentrating in the areas most likely to be fished. While not explicit in the model, as it is based on observed behaviour, and as fishers do not know in advance the actual conditions they are facing, then there exists the likelihood that the derived effort allocation will be sub-optimal. That is, error in decision making is implicit in the model. This explains the result that profits can increase as a result of a closure or management intervention if fishers are operating in a less than optimal way initially, and the management intervention provides – inadvertently – incentives to change location that results in higher profits. This, of course, is case specific and will be determined by the efficiency of fishers' location choice.

In contrast, the DSVM determines an optimal allocation of effort across the fishery assuming perfect knowledge. The DSVM also takes into account the opportunity cost of using the effort quota – something that is ignored by the RUM which treats each trip totally independently.

While an advantage of the RUM is that it uses trip level data for both the estimation of the model parameters and simulations, developing the models with many location choices also creates difficulties in the RUM framework. For each observed choice, an estimate is required of what might have happened in each alternative choice. Average catch information from other vessels which fished in these alternative locations at the same time can be used, but the resultant data matrix is considerable. Compiling such a data set is a non-trivial task. Further, location choices are restricted to only those observed at the time, so there is no potential to consider policies that are outside the historic data, even if they might have greater benefits.

A final difficulty is that fishing effort has to go somewhere in this modelling framework (as fishers cannot opt not to fish), even if in doing so causes economic losses to the fisher and industry. The substantial losses estimated in the scenarios examined are likely overestimated, as fishers would most likely choose not to fish rather than incur these losses. In the DSVM, not fishing was an option, resulting in lower reductions in profit than the RUM.

6.2 Incentives vs closures

The relative issues with each modelling approach notwithstanding, each model provided a basis for comparison of the spatial redistribution of effort and its effect on relative profitability in response to spatial incentives. The response to incentives was compared with to that under an area closure, and to the baseline scenarios.

Within each of the random utility and dynamic state variable modelling approaches, overall fishery profitability shows no consistent pattern with the increasing strength of the management measure. There was instead high variability with year, with incentive level, by port and by management area. The year, port and management area variability are likely due to the high spatial and temporal heterogeneity of the fishery, both in terms of relative fish availability and costs. The profitability response to incentives, however, is non-linear and complex, and, in some instances, counter-intuitive. In the case of the DSVM approach, the nature of the price game is such that vessels are effectively confronted with a new regime in response to a management scenario, and adapt accordingly. Together with the highly responsive nature of this model, this implies that overall profitability is typically not greatly compromised under spatial incentives or closures as all vessels in the fishery find the behaviour that generates the highest overall profit in the new management regieme.

The reduction of effort in the area of interest generally did correlate with the increasing strength of the management measure, although for the DSVM where baseline effort was already low in the area of interest, any measure resulted in the relocation of all, or almost all of this effort. The inference is that, although the measures perform as anticipated to reduce the relative effort in the area in which they are applied, the response of the fishery as a whole in terms of its profitability is not straightforward, as this is dependent not only on the strength of the management measure, but also on when and where it is applied (and, as such, the baseline effort distribution, and relative availability of fish), and the flow-on effects of the effort relocation on market prices.

It follows that, irrespective of the modelling approach used, there is no clear "winner" in terms of an optimal spatial management strategy for the fishery, and no general advice emerges as to the relative benefits of spatial incentives (hook decrements) compared with area closures. Moreover, in some circumstances, closures or stronger incentives could actually result in higher fishery profitability than that experienced under baseline or low incentive scenarios. The main message is that the overall change in fishery profitability in response to a spatial management measure will depend on a combination of factors that interact in a non-linear manner.

Given this, it is more informative to consider sub-fishery responses, such as profitability changes by home port. Examining only the overall change in fishery profit can be misleading in that this may mask potential distribution impacts that occur within the fleet. The random utility model approach allows for results to be readily broken down by home port, while the simplified, coarser port structure assumed in the DSVM approach allows less disaggregation into sub-fleets. However, both approaches do show clear winner and losers under a given scenario, such that some general patterns emerge at a sub-fleet level. The implications are twofold: first, an overall gain to the fishery may come at the expense of one of its sub-sectors, and vice-versa; second, general patterns in response to management measures may be more readily apparent if these are broken down by home port and/or vessel type.

The high sensitivity of the fleet response to not only the magnitude but the location and timing of the management measure, as well as to the subset of the fleet (vessel type, home port) is apparent within each modelling approaches. However, an important additional observation is the lack of consistency in results *between* the modelling approaches under any given suite of scenarios, in spite of attempts to make the approaches as comparable as possible. One may, therefore, be tempted to draw the conclusion that neither model is valid, or to make a case that one approach is superior to the other. While acknowledging the fundamental differences in the approaches, and the respective advantages and shortcomings of each, interpretations in this direction neglect to appreciate that each model makes fundamentally different assumptions regarding fisher behaviour.

The DSVM approach assumes that fishers have perfect knowledge and adapt and "re-equilibrate" instantaneously, optimizing over all vessels and ports simultaneously, while also including the option of choosing to remain in port at any given time. Conversely, the random utility model assumes all boats must fish at all times, thus failing to consider opportunity cost. Additionally, modelled fishing patterns may only follow those observed historically (i.e. are constrained by the data). This confers a higher behavioural "viscosity" whereby fishers are effectively unable to adapt rapidly to new circumstances.

The two modelling approaches thus embrace two behavioural extremes: at one, a highly efficient adaptation to new conditions, with no constraints of past behaviour, and at the other, a reluctance to relinquish past patterns or habits, and an inability to consider opportunity cost. Given the lack of consistency in the fishing patterns that emerge in response to each approach, the challenge is less one of determining which is the superior, than to establish where, between these extremes, true decision making ability and behaviour lies. Further, fishermen almost certainly show disparity in their decision-making process, with some more efficient that others. Assuming that behavioural profiles can be established (for example, via questionnaires and the use of simulation games), the question of predicting responses to spatial management could be addressed by partitioning the fleet and evaluating the subsets using one or other of the approaches according to the behavioural category to which they correspond. Results from both approaches could then be combined to generate a fleet-wide response. Where behaviour lies in between the extremes, the DSVM model approach has the potential to be adapted to accommodate inefficiency, errors in decision making, and alternative definitions of utility. The random utility model approach is comparatively inflexible in this context.

6.3. Implications for spatial management in the ETBF

A key result of this study is that spatial input controls – including closures – have inconsistent outcomes in fisheries with a mobile resource. Given this uncertainty as to where the fish may be, a closure may result in economic benefits in years where it shifts fishers from areas with relatively low abundance to areas with higher abundance. However, as a fisheries management tool in an effort managed fishery, diverting fishers to areas of higher abundance may also come at a cost of higher exploitation rates.

A key advantage in this regard is the increased flexibility of a hook decrementation system compared with the all-or-nothing closure system. Hook penalties can be fine tuned during the season in response to unexpected spatial shifts in both the target and bycatch populations. Where exploitation rates appear higher than expected for target or bycatch species, the hook penalty can be readily adjusted to reduce the incentive to fish in these areas. Further, information is collected across the fishery as a whole enabling a greater understanding of the spatial stock dynamics to be developed. In contrast, information on relative stock abundance is not revealed in a closed area.

The impact of a closure varied considerably for different ports, largely depending on the costs of fishing elsewhere (both in terms of catch rates and steaming costs). In particular, the southern ports are likely to be severely affected by closures if these are on their main fishing areas due to a lack of nearby opportunities. These effects may have been exaggerated by the closure of the area for the whole year, but nevertheless a closure – even for part of the year – is likely to severely disadvantage these southern ports. While distributional considerations are not an important concern under the Commonwealth Harvest Strategy Policy per se, compliance is likely to be adversely affected, and implementation made more difficult if there are substantial distributional inequities. These areas are also likely to be affected by a hook decrementation system, but to a substantially lesser extent in comparison with the effect of closures.

A review of spatial management measures in the ETBF also identified a hook decrementation system as preferable to a system of area closures for economic, environmental and social reasons (Pascoe *et al.* 2009b).

6.4 The impact of a change to individual transferable quotas

This project commenced when incentives were being considered in context of a system of effort controls, primarily in the form of a total allowable effort system with individual statutory fishing rights in terms of gear (hook) units. Since then, a decision has been undertaken to move the fishery to an output control management system, primarily operated through individual transferable quotas (ITQs). Through ITQs, and their associated total allowable catch (TAC), limits on take of particular species – including bycatch species if the system extends this far – are directly controlled. In contrast, the hook decrementation system is an indirect control system aimed at providing incentives to change behaviour rather than limiting catch directly.

Being a direct control system, an ITQ system does have a number of advantages over the hook penalty system in terms of total catch, but unless TACs are set on a spatial as well as total level, or include bycatch species explicitly in the quota system, they may have some weaknesses also. Primarily, if the distribution of bycatch species is not uniform (as it is not in the case of the ETBF), where the quota is taken has consequences for the total level of bycatch of some species, particularly turtles and seabirds. A spatial TAC can help reduce this problem as catches in particular areas can be limited directly. However, spatial TACs also require a good estimate of where and when the target stocks will be in particular areas if they are to be economically effective. Changing TACs during the season is possible in response to shifts in relative abundance of the target (and bycatch) species, but is generally disliked by industry and managers.

These issues notwithstanding, the DSVM can be adapted to examine the possible consequences of spatial ITQs by changing the effort quota to a catch quota system. Further, the DSVM explicitly considers the opportunity cost of consuming quota (effort or catch) making it a more reliable modelling system. In contrast, the RUM doesn't easily allow for limits to be introduced, and even if the simulation model built around the RUM could be modified to allow for catch limits, the individual trip decision is still considered independent, so would not consider the opportunity cost of using quota in any one trip.

The RUM also does not allow for the possibility of quota trading and quota consolidation. From the results of this study, it might be expected that quota would move from some of the southern ports to the more northerly ports if TACs in southern parts of the fishery were reduced proportionally more. While the DSVM also does not allow for this at present, it is more easily modified to incorporate the potential for quota trading.

7. Benefits,

The key beneficiary of the project will primarily be AFMA and the management bodies (RAG and MAC) charged with managing the fishery, as the project has developed a number of modelling tools that can be used for further analyses. The ultimate beneficiaries will be the ETBF fishers who will benefits from improved management decision making as a result of the analyses. The direct benefit of this is less apparent given the change in policy towards ITQs. However, the modelling tools can be adapted to provide support for the management of the fishery under and ITQ system.

8. Further developments

Further developments of the models could include modification of the DSVM model to analyse the effects of different quota scenarios (e.g. spatial vs fishery whole quota, the use of bycatch quotas). While the RUM is less suited to ITQ fisheries than the DSVM, there are potential benefits in considering how the RUM could be included into a broader bioeconomic modelling framework. An advantage of the RUM identified in the study was that it did allow for the fact that fishers do not always operate in the best areas (although why this is the case is not easy to establish). Combining a RUM model with a bioeconomic optimisation model that incorporates a measure of opportunity cost may be a useful addition to the modelling toolbox being developed for the fishery.

9. Planned outcomes

The project has achieved all the planned outcomes in the original proposal. The project provided two mechanisms for predicting the impacts of SAFs on the fishery, and specifically on the choice of location by individuals and its economic impacts. The first, a statistical approach, used past fishing patterns to explain behaviour and extrapolated this to the effects of changes in the incentives facing fishers. The second, a mechanistic approach, derived individual behavioural rules basd on operating costs and expected revenues which were used to predict fishing behaviour.

The models were used to explore the impacts of different SAF structures, including their economic effects at the level of vessels, ports and the fishery as a whole. The ability to evaluate the likely redistribution of effort when SAFs are altered allows managers to anticipate ecological, economic, and social ramifications that may emerge due to these shifts. Had the decision to change the management system to ITQs not been taken, then the outcome would be of substantial use in managing the ETBF, both as a pilot analysis of the implications of the SAF approach, and as a tool for evaluating future modifications to the SAFs.

10. Conclusions

The purpose in the study was to assess the impacts of the hook decrementation system on the distribution of fishing effort and the economic impact on the fishery. The specific objectives relate directly to this purpose, in that it aimed to:

- develop a statistical (multivariate logit) model to predict the distribution of fishing effort in the ETBF;
- develop a process (a state-dependent behavioural) model of effort allocation for an input managed fishery; and
- evaluate the impact of a series of SAF scenarios on the distribution of fishing effort in the ETBF using statistical and state-dependent behavioural models.

All of these objectives were achieved.

The results of the analysis highlighted the strengths and weaknesses of the two modelling approaches. Both approaches have advantages and disadvantages in relation to the analysis of an effort control system such as the hook decrementation program examined, although in many regards the DSVM is likely to have greater potential for the analysis of an ITQ system.

Despite their differences, the key results of the two models were similar, that being that the impact of closures and hook decrementation systems vary considerably depending on where they are applied, when they are applied and how they are applied. Generally, a closure resulted in greater economic losses to the industry than a decrementation system, but this was not uniformly the case. Both models suggested that a hook decrementation system would result in effort moving out of areas where high penalties were applied, although the DSVM model results suggested a greater sensitivity to these incentive changes than the RUM model. In many cases spatial management also had distributional effects in the fishery, potentially even resulting in increases in profit for some vessels and ports concurrent with losses for other vessels and ports. The final results suggest that specific analyses of any proposed scenario would be prudent, as although outcomes are predictable they are highly variable depending on the exact design of the management scenario.

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Appendix 1: Intellectual Property

Not applicable.

Appendix 2: Project Staff

Main research team

- Dr Chris Wilcox (PI)
- Dr Natalie Dowling (developed DSVM)
- Dr Sean Pascoe (developed RUM and associated model)

Support with data analysis

- Dr Ana Norman (assisted in data preparation and RUM analysis)
- Dr James Innes (assisted in data preparation)
- Mr Tom Taranto (assisted in log book data analysis and mapping)

Appendix 3: Papers produced during the project

1. Pascoe, Sean, Chris Wilcox, Natalie Dowling and Tom Taranto 2010. Can incentive-based spatial management work in the Eastern tuna and billfish fishery? Paper presented at the *53rd Annual AARES National Conference, Adelaide*, *February 10-12, 2010.*
    a. A revised version of this is in preparation for submission to a peer-reviewed journal.
2. Natalie A. Dowling, Chris Wilcox, Marc Mangel and Sean Pascoe, Assessing Opportunity and Relocation Costs of Marine Protected Areas Using a Behavioral Model of Longline Fleet Dynamics. *Fish and Fisheries* (in submission).