Can incentive-based spatial management work in the Eastern tuna and billfish fishery?

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Abstract

The Eastern tuna and billfish fishery (ETBF) is currently managed through an input quota system based on individual transferable effort units (the number of hooks) and a total allowable effort level (i.e. total number of hooks) A spatial management policy based on a series of differential hook-penalties has been proposed as a flexible tool to discourage vessels operating in certain areas (e.g. those with high bycatch potential) and encourage operating in other areas (e.g. with less bycatch potential). In this study, the importance of catch rates per hook to location choice is assessed through the estimation of a nested multinomial logit model. Other variables in the model include distance to the location, prices of the main species, fuel prices and vessel characteristics. The effects of increasing hook penalties in key areas on fishing effort in those areas and elsewhere are assessed. Implications for vessel economic performance are also assessed.

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1.0 Introduction

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 conservation as well as fishery benefits (Pascoe *et al.* 2009). 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 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. Where effort is deployed has different implications for 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. These 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 will attract a high penalty rate, whereas other areas with little bycatch may 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, while those who chose 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). 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, a nested multinomial logit model is estimated to determine the importance of catch value per hook (VPH) on the location choice of fishers in the ETBF. From this, the effects of varying effective VPH on effort levels through inducing hook penalties in both high effort and low effort areas is examined. The impact on economic performance is also considered through estimating the proportional changes in total fishery revenue and fuel costs.

2. 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). 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).

Fishing effort is expended disproportionally over the range of the fishery (Figure 1a), 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.[1] The fleet is relatively homogeneous across the fishery (Table 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.

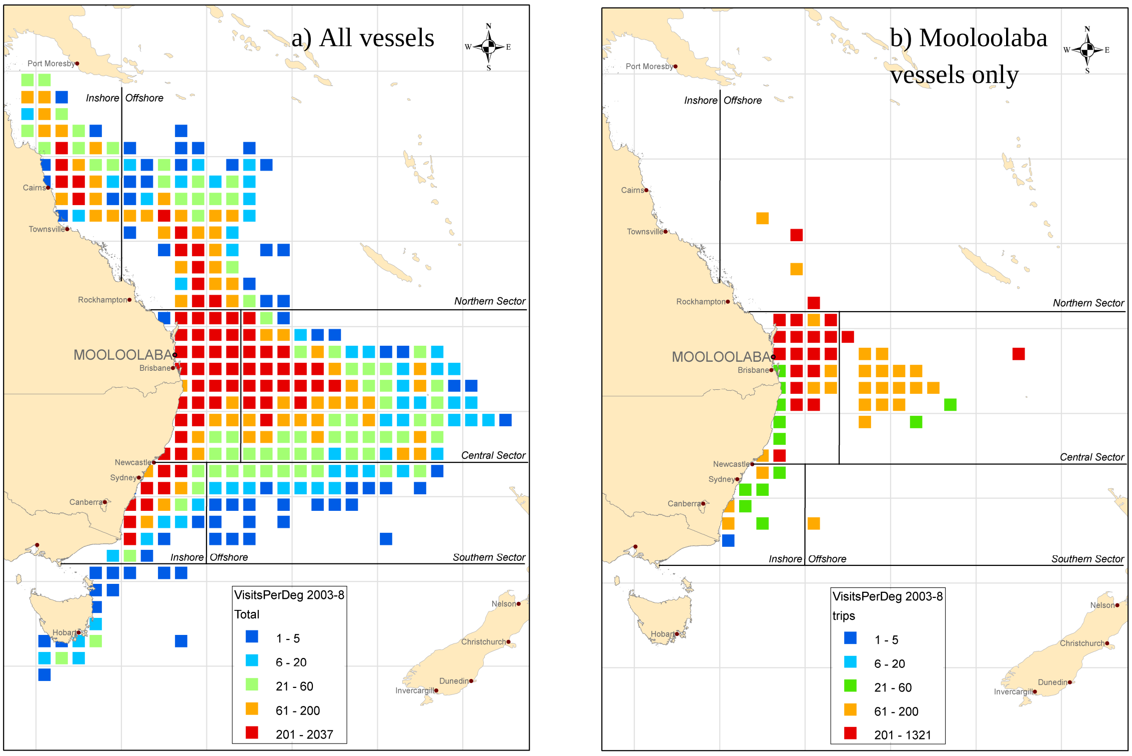

Figure 1. Distribution of total fishing days, 2003-08 (a) all vessels; (b) Mooloolaba vessels

Table 1. Characteristics of the vessels by general region (2003-08)

Region	Boats	Share of total trips	Length		Power		Hooks deployed	
			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

The largest single port is Mooloolaba (Table 1), located on the Sunshine Coast north of Brisbane. For practical reasons (given the substantial quantity of data involved), the analysis was limited to vessels fishing out of Mooloolaba. These vessels had a similar distribution of effort to the fishery as a whole (Figure 1b). Vessels operating out of the southern-most ports

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[1] The northern, central and southern sectors and their inshore/offshore delineations illustrated in Figure 1 were derived for the purposes of the analysis and do not reflect any management boundaries.

also operate in the southern bluefin tuna fishery. Hence, their share of total trips in the ETBF is substantially lower than those of the Mooloolaba fleet.

3. Modelling fisher location choice

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).[2] 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

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[2] 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).

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.

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

3.1 Multinomial logit and nested multinomial logit models

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

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

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

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

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. 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 2).

Table 2. 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.[3] 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.[4]

For the purposes of the model, each trip was allocated to a 1° 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 1). Areas with low observed effort levels (see Figure 1) were amalgamated with adjacent low effort areas, resulting in a total of 72 fishing areas. The magnitude of the data set, and the number of potential ports from which vessels could fish, increased the complexity of the data set required for the multinomial logit model. Consequently, only vessels operating from Mooloolaba were used in the model estimation. These vessels were active in 62 of the 72 fishing areas.

The key area variables used in the analysis were average value per hook, and the average distance to the home port (Mooloolaba) 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).

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

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

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,[5] 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.

5. Results

5.1 Nested multinomial model

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.[6] 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), suggesting a nested specification is more appropriate (Hensher *et al.* 2005).

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). 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

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[5] Other studies have used a dummy variable to identify data for vessels that did not fish the previous week (Holland and Sutinen 1999, 2000).

[6] 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).

migratory, largely following thermal eddies in the ocean.[7] 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 dynamic in other ways: relative prices between species have changed over the period of the data, while the availability of individual species varies considerably interannually, 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 little value on their past behaviour.[8] 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).

Table 3. Estimated NL model parameters

	All variables				Excluding "habit" variables			
Variable	Coeff	St. error	Coeff/ St.Er.	P[Z>z]	Coeff	St. error	Coeff/ St.Er.	P[Z>z]
Utility model								
VPH Week-1	0.188	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		

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[7] 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.

[8] 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).

The model estimated effort allocation was compared with the actual effort allocation observed in 2008 (Figure 2). 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.

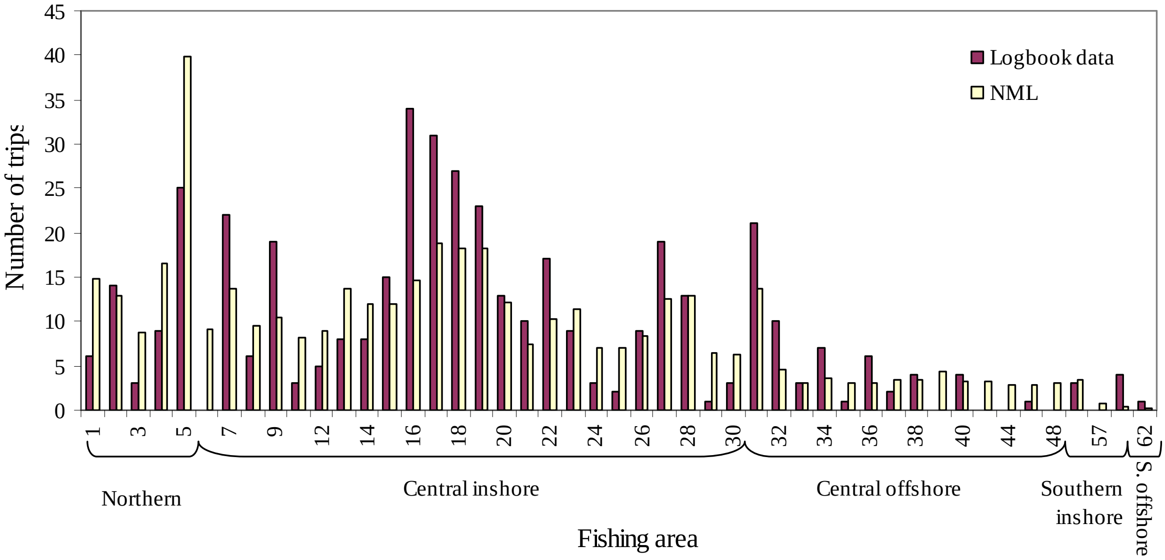

Figure 2. Actual and estimated distribution of fishing days, 2008

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).

5.2 Scenarios

The effect of a hook decrementation system on effort reallocation was estimated for two different scenarios to examine the effectiveness of the system in different areas. The sensitivity of these responses to fuel prices was also examined. Further, the effects of the hook decrementation system were also compared to those from a total closure of the areas. Only data relating to fishing trips for 2008 were used in the scenarios. The fleet was reduced substantially in 2005 and 2006 as part of a national fleet reduction program. The 2008 data reflects the current fleet situation, so provides a more meaning base for examining the effectiveness of the incentive based system.

In the first scenario, varying hook penalties were applied to four adjacent fishing areas (1^o grid cells) relatively close to port and characterised by high effort levels. The second scenario involved applying the penalties to four adjacent cells offshore. These were characterised by relatively low effort levels already. The inshore areas included in the scenario were also characterised by lower VPH than the offshore areas ($3.17/hook cf $4.70/hook), but also lower costs (the price*distance averaging 186 and 489 for the inshore and offshore areas respectively). These areas were selected to test the effectiveness of the incentive system under different cost/revenue conditions rather than representing any potential future policy implementation.

The impact of the effort reallocation on revenue and fuel costs was also estimated for each scenario. The fuel cost change was represented by the additional distance travelled as a result of the hook penalty, assuming a linear relationship between distance to fishing area and fuel cost. Revenue was estimated based o the number of days fished in each area, the average number of hooks used, the average number of days per trip and the average VPH.

In both scenarios, the proportional change in effort in the affected area was less than the effective change in VPH, indicating that effort allocation is relatively inelastic with respect to VPH (Table 4). The proportional response was greater in the inshore areas than the offshore areas. The offshore areas are primarily exploited by the larger vessels. From the multinomial model, these boats gain greater utility from operating in the distant locations than the smaller boats.

For the high effort area, both total fishery revenue and costs increased as a result of the effort reallocation, while both decreased when the penalty was applied to the offshore area. Fuel costs increased by a greater degree with the inshore penalty as vessels moved further offshore. With the offshore penalty, fuel costs and revenues changed by about the same degree. In both cases, the profit implications of the effort allocation are likely to have been relatively minor, although greater for the inshore (high effort) area than the offshore (low effort) area.

Table 4. Hook decrementation scenario results, 2008 data

Area scenario	Hook penalty scenario				
	1.1	1.2	1.5	2	3
Effective change in VPH (%)	-9	-17	-33	-50	-67
Inshore (high effort)					
• Change in days fished in affected area (%)	-5.24	-9.31	-17.44	-24.56	-30.81
• Change in total revenue (%)	0.18	0.32	0.60	0.85	1.06
• Change in total fuel costs (%)	0.59	1.04	1.95	2.74	3.43
Offshore (low effort)					
• Change in days fished in affected area (%)	-2.60	-4.63	-8.75	-12.42	-15.71
• Change in total revenue (%)	-0.01	-0.02	-0.04	-0.06	-0.07
• Change in total fuel costs (%)	-0.01	-0.02	-0.04	-0.06	-0.08

For comparison, the NL model was used to estimate the effects of fully closing the areas rather than applying a hook penalty. As would be expected, effort reduction in the areas was substantially greater than under the hook decrementation system, but the additional costs imposed on the fleet were also substantially greater, particularly for the inshore closure scenario (Table 5). In contrast, closing the offshore areas had little impact on overall fishery economic performance, with less than 1% change in total fishery profits. This suggests that closures may be relatively efficient management tools in areas of low effort, but in areas of high effort may impose substantial costs on the industry compared with incentive based systems.

Fuel prices in 2008 were substantially higher than previous years, and decreased by around 30% in 2009. As utility generally decreased with distance from port (reflecting the higher fuel costs involved in reaching the more distant areas), it would be expected that the higher fuel prices would have pushed the fleet inshore, potentially reducing the effectiveness of the hook decrementation system in these areas. The model was re-run with a 30% reduction in fuel prices (affecting the three distance-related variables for the inshore area only to test the sensitivity of the policy to fuel prices. Counter to expectations, effort tended to increase in the inshore areas and decrease in the offshore areas (Figure 3). From Table 2, the effects of price*distance is effectively positive for boats over 21m in length, and negative for boats less than 21m in length (i.e. 0.02*price*distance-0.418*price*distance/length >0 for length>20.8m and <0 for length <20.8m). This results in a reduced incentive for smaller vessels to fish offshore, and a higher incentive for larger vessels, as expected a priori..

Table 5. Closure scenario results, 2008 data

Area scenario	Closure areas inshore	offshore
• Change in days fished in affected area (%)	-100	-100
• Change in total revenue (%)	3.49	-0.35
• Change in total fuel costs (%)	10.92	-0.44

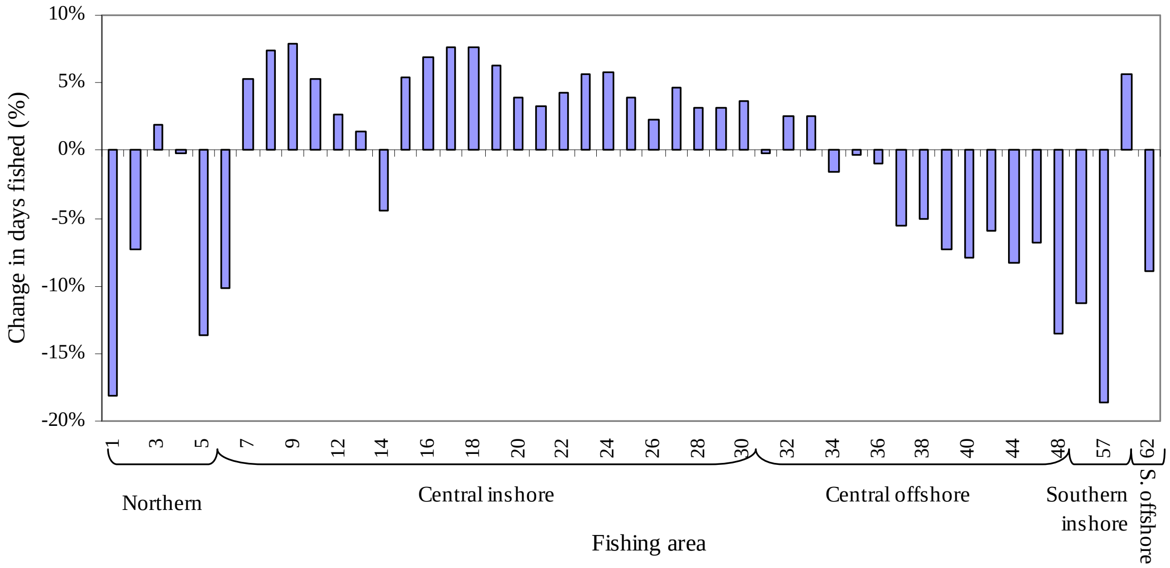

Figure 3. Change in days fished in each area due to a 30% reduction in fuel prices

The average length of Mooloolaba vessels is 22m (Table 1). While lower fuel costs may increase the probability of smaller vessels (<21m) venturing further from shore, larger vessels (more than half the fleet) would have a greater incentive to move inshore. This result is potentially an artefact of the model. However, the reduced fishing costs may also offset the lower VPH inshore, resulting in shorter total trips (including steaming time that was not included in the data) and potentially higher overall profits

The initial effort in the inshore areas to be subjected to the hook penalty increased from 70 to 75 days as a result of the lower fuel costs. However, the proportional change in effort in response to the hook decrementation system was similar to that in the scenario with the higher fuel prices (Table 6).

Table 6. Hook decrementation scenario results with lower fuel prices, 2008 data

Area scenario	Hook penalty scenario				
	1.1	1.2	1.5	2	3
Effective change in VPH (%)	-9	-17	-33	-50	-67
Inshore (high effort)					
• Change in days fished in affected area (%)	-5.17	-9.21	-17.26	-24.33	-30.55
• Change in total revenue (%)	0.20	0.35	0.65	0.92	1.16
• Change in total fuel costs (%)	0.61	1.08	2.03	2.86	3.58

6. Discussion and conclusions

Spatial management is becoming increasingly important as a fisheries management tool in Australia and elsewhere, particularly with respect to marine resource conservation (Pascoe *et al.* 2009). In most countries, spatial management has largely focused on marine protected areas (Wilen 2004), although there are a range of alternative spatial management tools that may achieve the desired conservation outcomes without a total closure of a fishing area. The hook decrementation system examined in this study shares similar characteristics to a individual habitat quota system, in that spatial penalties can be assigned to effort expended in particular areas to encourage movement elsewhere (Holland and Schnier 2006).

The results of the analysis suggest that a hook decrementation program is likely to be more successful in terms of effort reallocation when the penalties are applied to high effort areas than low effort. The attraction to the latter is fairly limited (hence the low level of effort), so making these areas less attractive is likely to have less of an impact. Conversely, high effort areas are attractive either due to their high VPH or low costs of access. In the case of the scenario examined above, the effort in the inshore areas was driven by both the low access cost and the VPH, which was also low relative to more offshore areas. Altering the effective VPH (i.e. increasing the opportunity cost of the hook quota consumed) in these areas resulted in a less than proportional decrease in fishing effort (with an implicit elasticity of around 0.5). In the offshore areas where access costs were substantially higher, the location choice by those vessels that fished there appeared to be less related to VPH than other factors, resulting in a more inelastic effort response (an implicit elasticity of around 0.25) to the hook penalty. Given that these areas are not substantially "attractive" in any case, imposing a hook penalty has lesser impact than in the more "attractive" areas.

Several forms of bycatch problems exist in the fishery, both in inshore and offshore waters. Interactions with turtles, while occurring across the fishery, are highest in areas close to nesting beaches, particularly in the northern part of the fishery. Interactions with seabirds occur in the central offshore zone (fleshfooted shearwater) and southern inshore zone (albatross). These areas are generally characterised by high effort levels as they also correspond to key tuna grounds at certain times of the year. Given this, a hook decrementation approach may help reduce fishing effort in the key interaction areas, although from the model results a high penalty may need to be imposed to result in a substantial effort reduction.

Only a hook penalty was applied in the analysis. Potentially, hook "rewards" could also be applied to attract effort to particular areas. The Faroe Islands' individual transferable effort quota system provides incentives for vessels to fish in offshore areas by allowing each quota day to equal three fishing days in these areas (i Jakupsstovu *et al.* 2007). Similarly, a hook penalty of less than 1 could be applied in areas where bycatch was relatively low to encourage fishing in these areas.

The model has several limitations, not the least of which is the availability of data. Expectations in the fishery are likely to be affected by sea surface temperature, and including this in the analysis may have improved the model fit. Heterogeneity in risk preferences has also not been considered, and this have been shown to affect location choice elsewhere (Mistiaen and Strand 2000). The analysis treats each trip as an independent event, and the location choice is based on the prevailing conditions only. While this is seen as an advantage of the NL approach in most cases (Smith 2002), with an effort quota, trips are not completely independent as hook units used in one trip results in less quota being available for use in the subsequent trips. In such a case, the response to the hook penalties may be greater than estimated using the model as the opportunity cost of using the additional hook units in the penalty areas is not fully considered.

The analysis was also undertaken only for one fleet (defined by port) operating in the fishery. More southerly fleets may be more or less responsive to the economic incentives created by the policy, as they face a difference set of potential locations, with different costs of access. Analysis of these other fleets is still to be completed.

Despite the potential model limitations, the model results suggest that a hook decrementation system has potential as a spatial management tool to redirect fishing effort from sensitive areas to less sensitive areas. However, high penalties may need to be applied to encourage effort reallocation. For some areas, closures may still be considered necessary if bycatch rates are unacceptable even at lower fishing effort levels. Closures are effective as a conservation tool, but as seen from the model results may impose substantial costs on the fishery, even if effort can reallocate. However, in many cases, effort reduction rather than total exclusion may be sufficient to achieve the conservation objective, and a hook decrementation system allows the level of effort reduction to be "fine tuned" through changing the penalty structure.

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