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Assessing opportunity and relocation costs of marine protected areas using a behavioural model of longline fleet dynamics

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Abstract

Increasing use of spatial management tools in fisheries requires an understanding of fleet response, and in particular to where displaced fishing effort is likely to move. We develop a state-dependent decision-making model to address the spatial allocation of effort in an Australian tuna longline fishery. We assume that fishers have an economic objective in deciding where to fish, but that decisions in any period are also influenced by the remaining quota held at the time of the decision. Key features of the model include endogenous price dynamics, a moving stock and a competitive pool of different vessel types operating from different port locations. We utilize this model to illustrate fleet responses to marine reserves and limits on fishing effort. The results illustrate that the model framework provides advantages over statistically based models in that decisions made in response to the imposition of a reserve are not consistent with a proportional reallocation of effort. Rather, the stochastic dynamic model yielded an overall profit level of ~4% higher relative to scenarios with no reserve. Incorporating the opportunity cost of a quota into the model resulted in an optimal utilization of effort, in which effort was concentrated in time periods and locations yielding maximized profit. Under a low level of effort relative to the season length, the model indicated an overall profit level 43% greater than the highest obtained when the same level of effort was applied solely within any given quarter of the season.

Keywords Fishery fleet dynamics, location choice model, spatial fisheries management, state-dependent model, stochastic dynamic programming, tuna longline fishery

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Introduction

Fisheries management typically focuses on the sustainable exploitation of target species, but the potentially negative effects on, for example, non-commercial species and/or habitats, should also be acknowledged and incorporated (Branch *et al.* 2010; Zhou *et al.* 2010; Hobday *et al.* 2011). Marine resource management is characterized by multiple objectives that encompass the sustainable use marine resources by competing groups, such as commercial and recreational fishers, maximizing their economic values while maintaining or enhancing conservation and other social values (Pascoe *et al.* 2009). Traditional effort and quota controls often are unable to realize the full set of objectives on their own, because they typically involve a trade-off between environmental and economic objectives (Campbell and Dowling 2005). Moreover, heterogeneity in the allocation of the resource lends itself to spatio-temporal management measures (Pascoe *et al.* 2009). Consequently, spatial management is receiving increasing interest in fisheries as an instrument to integrate biodiversity conservation, resource extraction and recreational use (Crowder *et al.* 2006; Douvere *et al.* 2007; Douvere 2008; Douvere and Ehler 2008; Fock 2008; Dunn 2010; Lubchenco and Sutley 2010), while also enhancing economic and sustainability objectives. Spatial management encompasses a wide range of measures, including both input controls (e.g. area closures, limits on fishing effort in different regions) and output controls (e.g. spatial catch quotas) (Dunn 2010; Gaines *et al.* 2010; Little *et al.* 2010; McCook *et al.* 2010; Parnell *et al.* 2010; Robb *et al.* 2011).

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 (Fig. 1). The commercial fishery is dominated by 55 longlining vessels that operate year-round (Campbell 2007). The principal target species are yellowfin tuna (*Thunnus albacares*, Scombridae), albacore tuna (*Thunnus alalunga*, Scombridae), broadbill swordfish (*Xiphias gladius*, Xiphidae), bigeye tuna (*Thunnus obesus*, Scombridae) and striped marlin (*Tetrapturus audax*, Istiophoridae) with the total catch of these five species in 2006 being around 6500 tonnes (Campbell 2007). The fishery interacts with the threatened species of seabirds, turtles and sharks, and with the southern bluefin tuna commercial and striped marlin recreational fishery, with the interactions typically occurring in distinct spatial regions (Griffiths *et al.* 2010; Trebilco *et al.* 2010; Hartog *et al.* 2011). ETBF is therefore an ideal case-study for spatial management, and the management for the fishery is currently being revised to incorporate spatial management measures. In 2007, the main albacore fishing area was closed to new entrants, and the Australian Fisheries Management Authority introduced a total allowable catch (TAC) for this area.

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 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 and often unintended consequences (Fulton *et al.* 2011), which necessitates more rigorous bioeconomic modelling of management scenarios (van Putten *et al.* 2011). Evaluating the potential effectiveness of alternative spatial management options 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

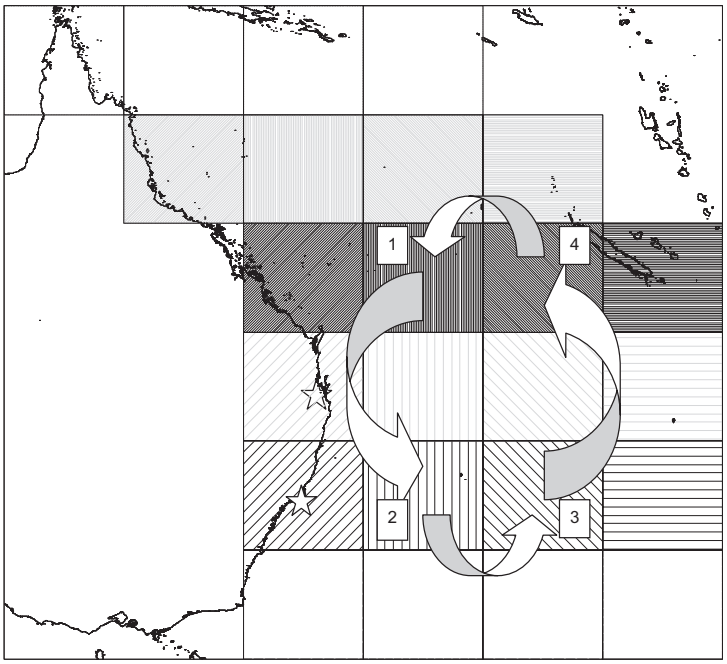

Figure 1 Map of Australia showing area of fleet operation and indicating regions, where each line colour (black or grey), shading angle and shading density is used as a unique identifier of the regions in subsequent plots. Regions are indexed by (latitude code, longitude code). Star shapes indicate the port latitudes (2 and 4), and the arrows and numbers indicate the movement of the centroid of the fish stock at quarterly intervals over the time series.

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 (e.g. Gillis *et al.* 1995a,b; 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,b). 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 (e.g. Sanchirico and Wilen 1999; Smith and Wilen 2003; Dalton and Ralston 2004; Smith *et al.* 2009).

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. That is, given the characteristics of the area and the fisher, future location choices can be predicted based on historical precedence (e.g. Wilcox *et al.* 2010). Most previously cited studies applied some form of the random utility model to model individual vessel behaviour (Bockstael and Opaluch 1983; Eales and Wilen 1986; Holland and Sutinen 1999, 2000; Curtis and Hicks 2000; Smith 2002; Wilen *et al.* 2002; Hutton *et al.* 2004; Pradhan and Leung 2004; Marchal *et al.* 2009; Wilcox *et al.* 2010), although more recent analyses suggest modelling behaviour at the fleet level may be more reliable in determining responses out-of-sample (Smith 2002).

In contrast, the 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 purported decision-making process approximates the natural situation with good fidelity.

While both approaches have merit, the mechanistic approach may be more useful in the context of estimating fishery responses to new management regimes, because it does not depend on historical patterns for its predictive power (e.g. Bue *et al.* 2008). 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). The lack of dependence on historical patterns 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 depends not only of the relative catch rates in that time period but also of the opportunity cost of using the quota now rather than later. That is, fisher 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, when used for prediction, the statistically derived approaches, such as random utility models, are often unable to adequately address these elements of spatial management (Wilcox *et al.* 2010). For example, if a fishing area is removed (representing a closure), the statistical models will typically predict one outcome – a proportional increase in effort in the remaining areas (by each individual fisher), assuming that the portion of effort previously dedicated to the closed area is reallocated equally among the open areas. 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 (e.g. Goni 2006), commonly termed 'fishing the line' (McClanahan and KaundaArara 1996; Kellner *et al.* 2007,). Unless the statistical method explicitly considers density of target species around a reserve according to production, connectivity and dispersal distance, it will be unable to predict a 'fishing the line' response.

Developing mechanistic models requires more understanding of the factors driving the behaviour of the fleet, which we consider to be a good thing, although this is often difficult to validate for situations not previously encountered (e.g. a new management regime). However, assuming fishers follow some form of economically rational behaviour (although see Holland 2008 for a review), models based on individual profit maximization or 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, which 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. It is important to note, however, that the state-dependent decision-making model developed here assumes fishers have perfect information and are able to immediately adapt to changing circumstances. It therefore represents an 'upper bound' on the type of response that may be invoked by the introduction of spatial management measures.

In this study, we use a state-dependent modelling approach to address two questions central to spatial management in marine systems. First, how do predicted fishing location decisions change if we consider opportunity costs. Second, what do these changes imply for predictions about how fishers will respond to management changes, particularly changes in spatial management. We develop a model to address the spatial allocation of effort in a fishery, based approximately on the Eastern Tuna and Billfish Fishery (ETBF), the tuna longline fishery off the East Coast of Australia. The model includes key characteristics of the fishery including fluctuating catchability because of migration of the target species, prices influenced by supply in the market and individual quotas on effort. We utilize this model to investigate (i) whether predicted location choices change as operators are allowed longer time horizons over which to fish (effectively changing their opportunity costs) and (ii) how predictions of effort redistribution by vessels differ from predictions that would be made using a statistical model of vessel location choice.

Methods

We developed 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. We utilize information from the Eastern Tuna and Billfish Fishery (ETBF), as a template test case for the model, but we make simplifying assumptions that may not directly reflect the true dynamics of the fishery. Most immediately, we simplify the ETBF as a single-species fishery targeting swordfish. These assumptions were made both for reasons of computational efficiency and because of the emphasis of the work being on the modelling approach used.

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 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. Vessels set lines called shots. Consistent with the operations of longline vessels (Campbell 2007), we assume that one shot equates to 1 day of the season, so that laying x shots requires x days. As days will be lost because of weather conditions and social demands, there is an overall upper limit on the number of shots per fishing season.

A model for state-based decision-making in an effort quota fishery

To begin, and for purposes of model simplicity, we consider a hypothetical single-species fishery, operating out of one or two ports and comprising 24 regions (Fig. 1) with no stochasticity (Table 1).

The key parameters that characterize the habitat are the following:

$N_{i,j}(t)$: 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 because 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 degraded 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)

We consider three different kinds of vessels (Table 2) characterized by the following:

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. This is a fixed quantity defined according to vessel capacity. As one shot typically takes 1 day to complete, lower-capacity vessels with shorter maximum trip durations

Table 1 Fishery parameterization.

Quantity	Value	Detail
δ	1	Amount by which effort will be degraded in each spatial cell fished (constant for these examples)
Number of spatial cells	24	longitude 1–4, with 0 = port and 4 furthest offshore latitude 1–6, 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 2

Table 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.

have a corresponding lower maximum number of longline shots that can be undertaken during a trip

ρ: the unit travel cost per vessel

E_{max}: the maximum number of shots per season allocated to each vessel. We assume that the number of longline hooks (clips) is constant for any shot, meaning that the effort quota could alternatively be allocated in terms of hooks, because all shots count equally against the quota

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 (Campbell personal communication), in which the higher-capacity faster vessels, which are able to make more shots per trip, are typically more expensive in terms of travel and shot deployment.

We incorporated range limits for lower-capacity vessel types by assuming a stepwise cost per unit travel function. 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 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. Although the range of the lower-capacity vessels could have been defined in a less arbitrary manner, the range was chosen so that it did not exclude the central fish density from potentially being reached by the lower-capacity vessels, even when this was further offshore.

Other parameters are

$\rho(t)$: the (species specific) unit price for landed fish

c: the cost per shot (recalling that the number of hooks was assumed to be constant across shots)

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

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

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, in 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 latitude i longitude j for vessel type b operating out of port $h, \pi_{i,j}(t, x, b, h)$ is

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

As 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 article. It

should be noted that this equation makes the simplifying assumption that all shots are equal across vessel classes, such that if vessels visit the same region and expend the same amount of effort, the lower-capacity vessels will be more profitable for that trip, but the trip will take longer. Additionally, the lower-capacity vessels will be worse off if the most profitable option is to set more shots than their trip maximum specifies. 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 port). If a vessel remains in port, it is assumed to do so for 1 day, so that t is incremented by one, after which the decision of where to fish is made again. Staying in port allows a vessel to get 'in phase' with the oscillating catchability and thus avoids the expenditure of capital when catchability and/or price is low. To begin, 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:

$$q(t) = 0.1\sin(0.2\mathrm{t}) + 1$$

Given that this is a simple, single-species model, we use this known association with moonphase to model swordfish catchability, but we acknowledge that this does not encompass the full range of considerations related to catchability of target species in this fishery. 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,

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

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)

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

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, which also determines the optimal fishing region $i^*(e, t)$ and the optimal number of shots $x^*(e, t)$ that yield the maximum accumulated profit. As 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, 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 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

$t \leq 30$: $i_P = 4$, $j_P = 2$
$30 \leq t < 60$: $i_P = 2$, $j_P = 2$
$60 \leq t < 90$: $i_P = 2$, $j_P = 3$
$t \geq 90$: $i_P = 4$, $j_P = 3$

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 enough time scale in a specific location. It is nevertheless a simplifying assumption that, while potentially applicable to some species within the fishery (and

assumed true here for swordfish), may not apply to all target species. The Eastern Tuna and Billfish Fishery Annual Status Report (2008) considers triggers to close areas if the monthly quota for certain species, such as striped marlin, has been reached, to limit localized depletion of the resource.

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 the mean price (specified as a constant). In this case, we set $\overline{p}$ = 8.0 dollars based on a weighted average of yellowfin, albacore and billfish prices from 1996 to 2007. (http://www.abare.gov.au/publications_html/afs/afs_09/09_FishStats.pdf).
2. We solve Equation 4 for each vessel type from each port, using the 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 landings under the current price trajectory. We assume that price is a function of the total volume V_t of landings by all vessels each time step and generate a new price trajectory according to

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

where f is the price flexibility. 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). For calculations, we set $|f|$ = 0.1, consistent with other tuna modelling studies in the region (Hannesson and Kennedy 2009). $\overline{V}$ 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: $p(t) = p(\mathrm{V}(t))$.
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. 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. As a metric for comparison of the two trajectories, we use

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

where $p_b(t)$ is the price trajectory used in the SDP, and $p_f(t)$ is the price trajectory generated by in the forward simulation.

Stabilizing the dynamic game

For cases with more than one vessel type and/or port, we stabilized the dynamic game (Houston and McNamara 1999; Clark and Mangel 2000) by the method of errors in decision-making. To do this, we assigned a probability to each region (latitude index i and longitude index j) proportional to its profit

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

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

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

where σ is a tuning parameter that measures how important it is to be near optimal. If this is very large, then the probabilities will be uniform. If it is very small, then all vessels will concentrate in the optimal location. For computations, we use $\sigma = 1 \times 10^3$ (noting that Δ ranges from 0 to $\sim 2 \times 10^6$, but is generally of the order of 1×10^5 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 four 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 30 days, a duration that almost equates to the available effort (recalling that one set equates to 1 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 compared the resulting modelled distribution of effort with that which would have occurred via a statistical model: the equal spatial distribution of effort formerly occurring in the closed area. The area ($i_P = 2$, $j_P = 2$) was selected as the area to be closed, as the results showed this to be the area 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.

Results

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, suggesting effort was inversely proportional to catchability. This implies fishers have real-time knowledge of the market dynamics, which is unlikely to often be the case. It emphasizes how the dynamic state variable model assumes that fishermen take a seasonal view of the fishery and

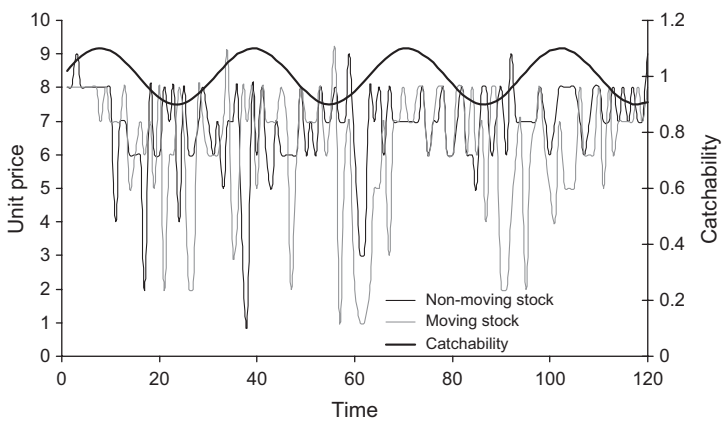

Figure 2 Overall price and catchability versus time for (i) case 2, aggregated across the 2 ports and 3 vessel types where fish are stationary and (ii) case 3, aggregated across the 2 ports and 3 vessel types where fish are moving quarterly.

market, as opposed to having a shorter time horizon directly associated with their bills.

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 because of the variation in the volume of landed catch throughout the season (Fig. 2). In comparison with 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 (Fig. 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.

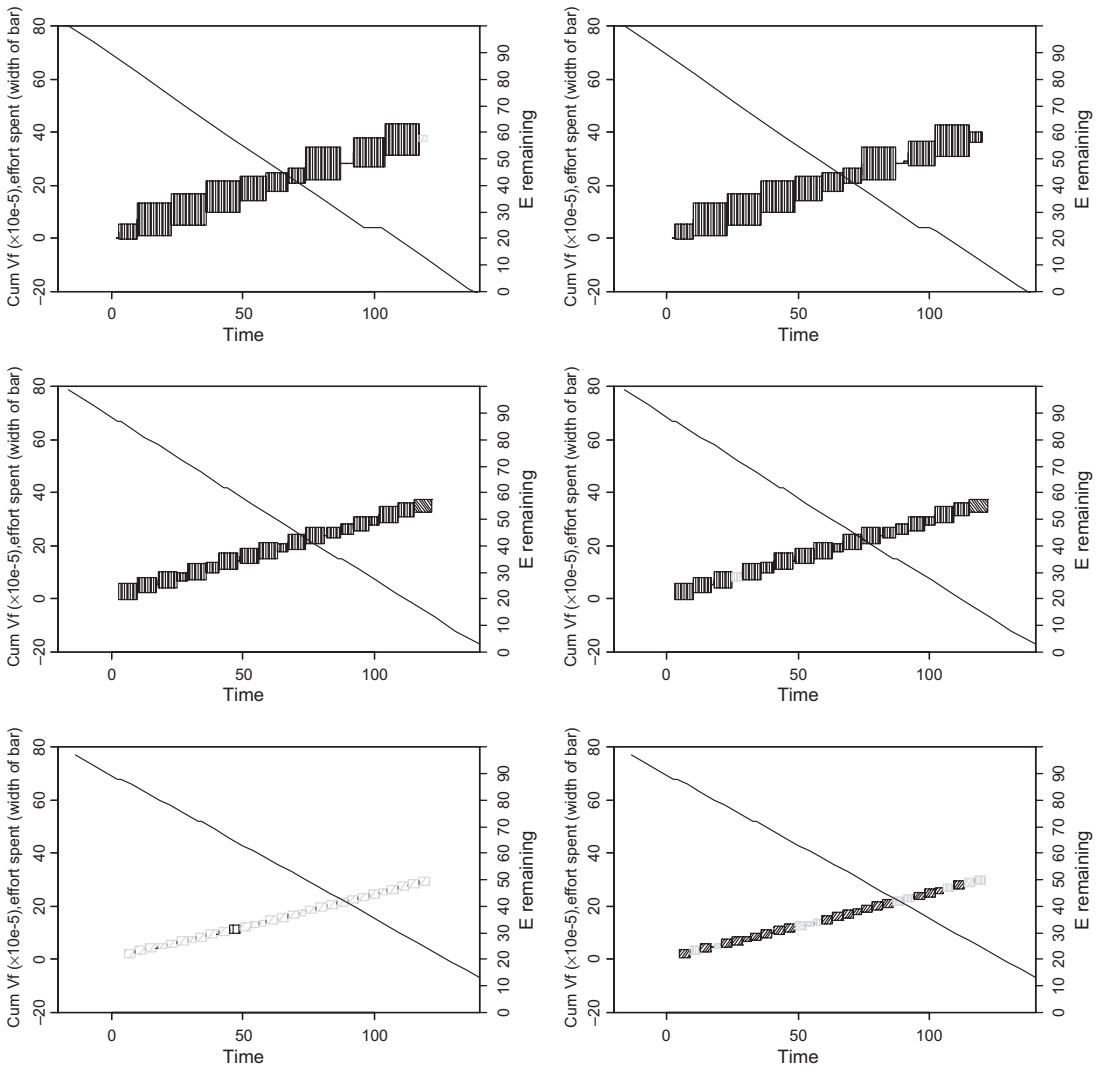

Figure 3 'Ribbon plot' showing time series of cumulative profit and remaining effort for each combination of 2 ports and 3 vessel types where fish are stationary, for one Monte Carlo realization. The height of the coloured bar equals the effort spent on the trip (with the cumulative profit at the midpoint), while the width equals the duration of the trip. The colour equates to the area visited on the trip, as per Fig. 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.

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 to 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 (Fig. 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 (Fig. 2). All vessel types did show similar patterns, in terms of making continual trips with effort close to or equal to the maximum permitted per trip, to those seen in case 2 (Fig. 4). However, while vessel type 1 (the

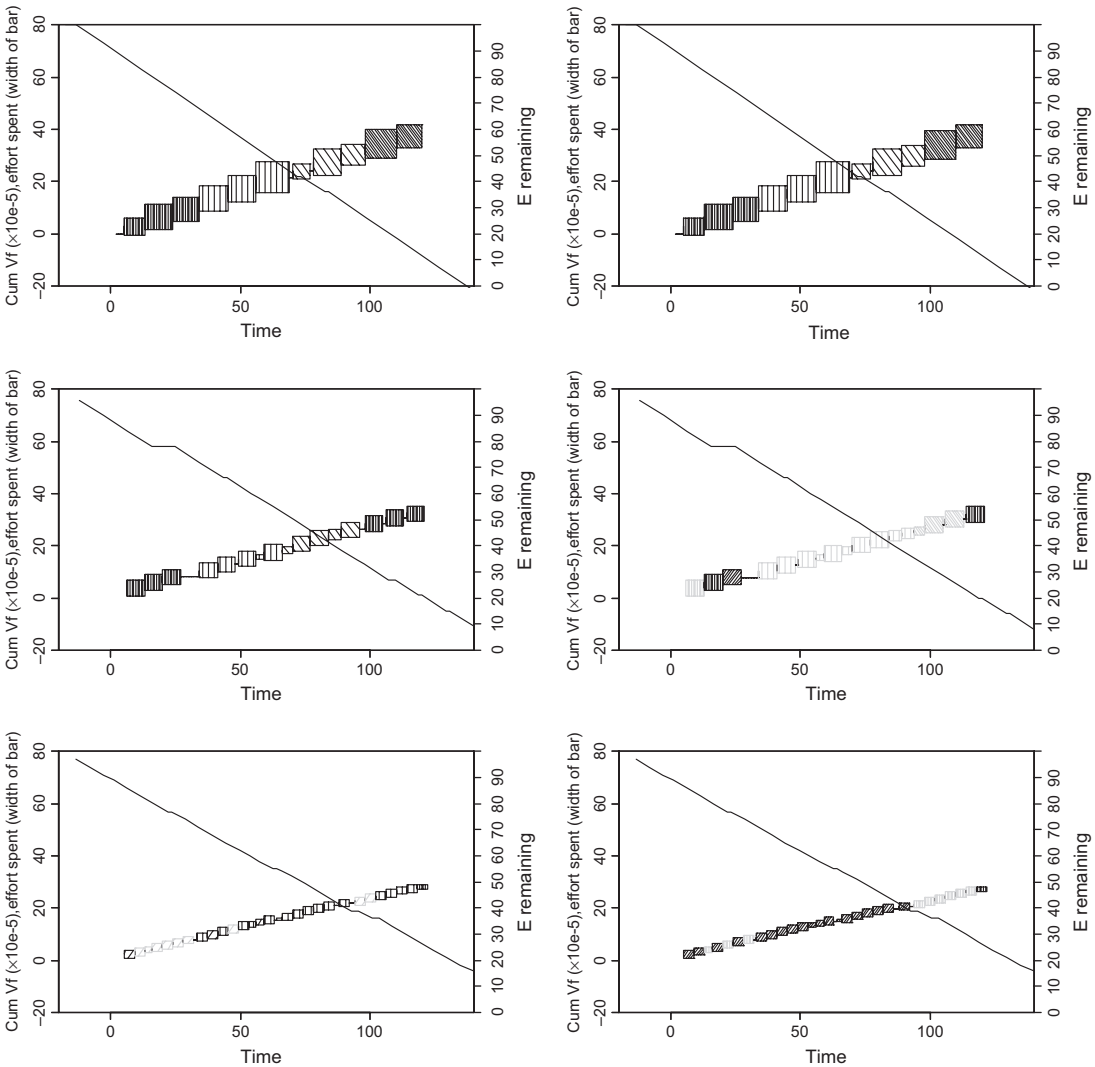

Figure 4 'Ribbon plot' showing time series of cumulative profit and remaining effort for each combination of 2 ports and 3 vessel types, where fish are moving quarterly, for one Monte Carlo realization. The height of the coloured bar equals the effort spent on the trip (with the cumulative profit at the midpoint), while the width equals the duration of the trip. The colour equates to the area visited on the trip, as per Fig. 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.

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 (Fig. 4). In general, total profit decreased with decreasing vessel capacity (Table 4).

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 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

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 four 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) and showed little variation between vessel types and ports relative to case 3 (Table 4). 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), and this occurred irrespective of

Table 4 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	3.750×10^6	3.237×10^6	2.812×10^6	3.741×10^6	3.200×10^6	2.719×10^6
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%

vessel type or port (Table 4). 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. This is the best indication of the ability of the modelled fleet to consider opportunity cost, as trips during this time would be relatively less profitable. 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 (Fig. 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 (Fig. 5 vs Fig. 4))

As described previously, closure of the region ($i_P = 2$, $j_P = 2$) is likely to cause maximum perturbation to the dynamics of the fleet. Relative to the

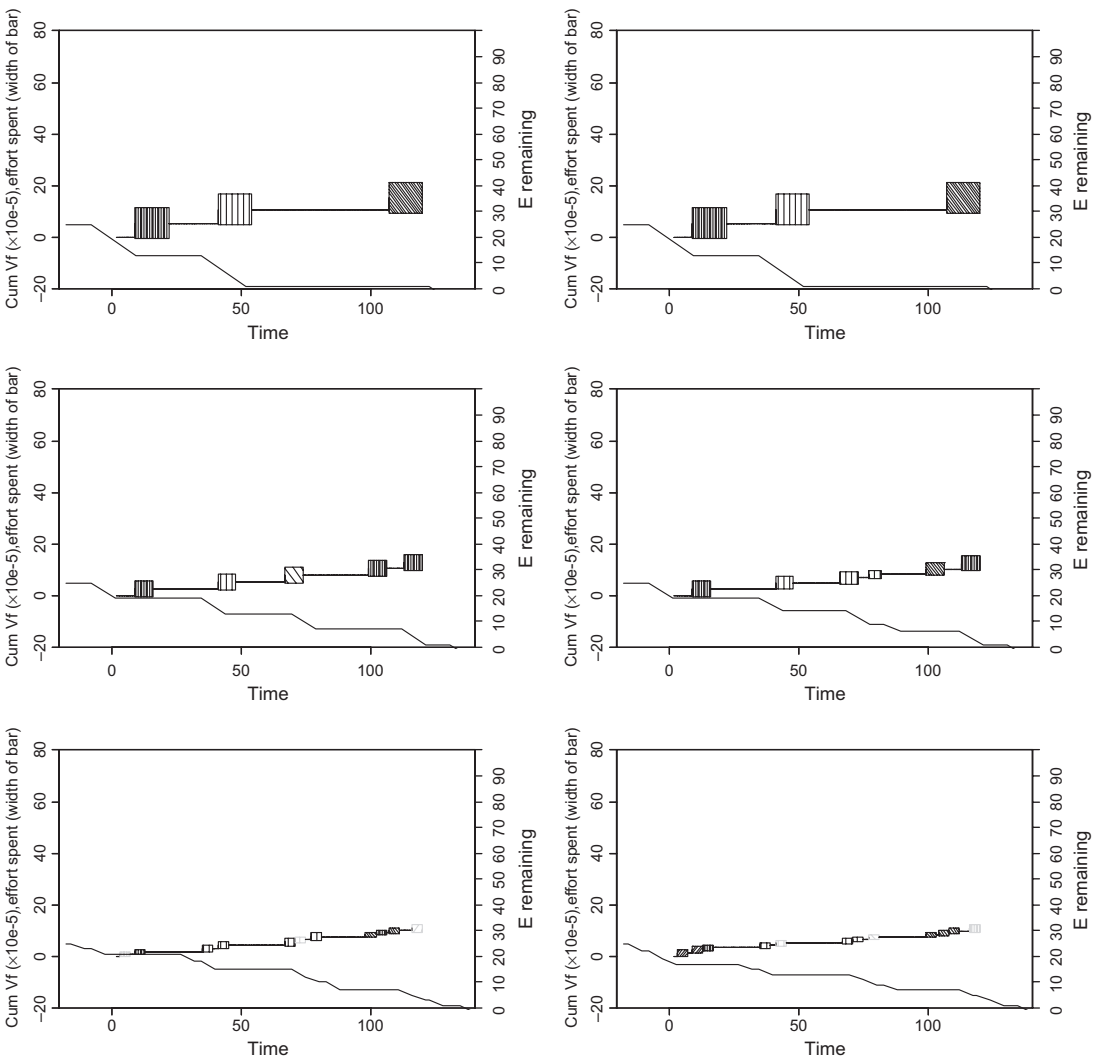

Figure 5 'Ribbon plot' showing time series of cumulative profit and remaining effort for each combination of 2 ports and 3 vessel types, where fish are moving quarterly and *Emax* = 25, for one Monte Carlo realization. The height of the coloured bar equals the effort spent on the trip (with the cumulative 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 Fig. 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.

spatial effort distribution from case 3 (Fig. 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 these adjacent cells in the absence of the closure (Fig. 7). 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 another key difference between this stochastic dynamic state variable approach and statistical approaches such as random utility models: the former predicts outside of the previously existing data, one of the dangers of purely statistical models. Statistical approaches would typically redistribute effort that had previously been dedicated to the closed region equally 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). 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 4).

Discussion

This is the first time a stochastic dynamic programming (SDP) model has been developed to predict the spatial and temporal distribution of effort in a fishery with the incorporation of a price game. To be sure, SDP models have been used in fisheries to investigate discarding and high grading behaviour in trawl fisheries (Gillis *et al.* 1995a and 1995b) and in terrestrial conservation ecology to determine the optimal choice a manager should make at each time step to minimize revenue foregone by not harvesting timber while maintaining a given population of birds (Doherty *et al.*1999). However, they have not been used in the context of evaluating fleet responses to underlying stock dynamics in a competitive context.

The state-dependent decision-making model developed here provides insight as to price dynamics and the spatial and temporal distribution of effort. The key assumptions of the model are that utility is approximated by profit and that effort allocation remaining at a given time in the season is an

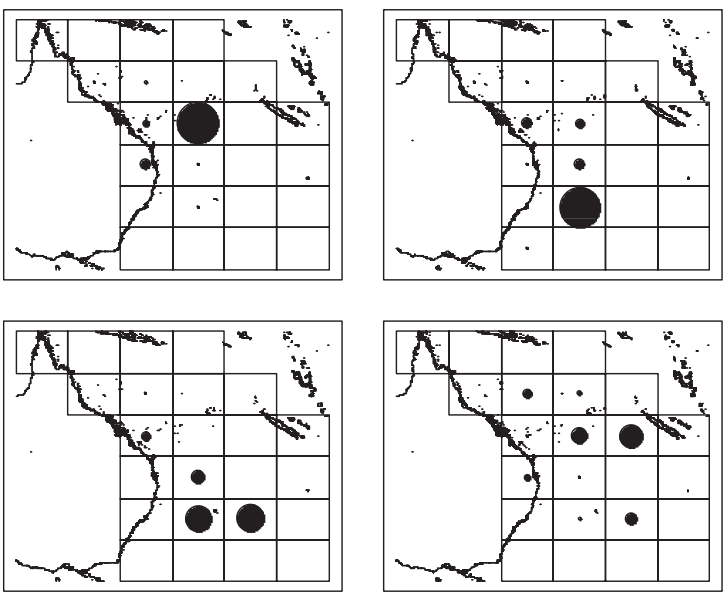

Figure 6 Spatial distribution and relative magnitude of total effort for case 3 (2 ports, 3 vessel types, quarterly fish movement) by quarter (each panel).

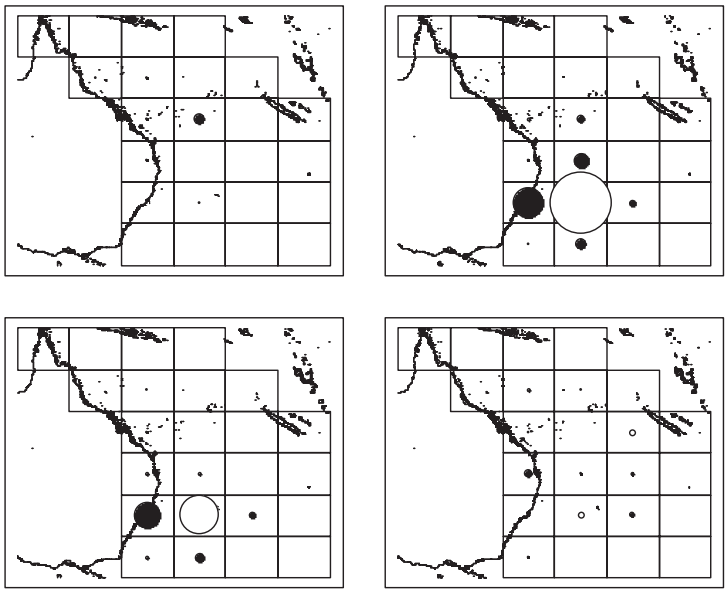

Figure 7 Spatial distribution and relative magnitude of the differences in effort for 2 ports, 3 vessel types, quarterly fish movement when region $i_P = 2$, $j_P = 2$ is closed, by quarter (each panel). Black circles indicate a relative increase in effort with the closure of region $i_P = 2$, $j_P = 2$, while open circles indicate a relative decrease.

appropriate state variable. The model in its current format has enabled us to evaluate fleet responses to opportunity cost and to enable prediction outside the data in evaluating the response to the imposition of a simple area closure, in the context of fluctuating catchability, vessel competition and seasonal migration of the target species. It could thereby provide a means for evaluating alternative spatial management regimes imposed on effort allocations in a fishery such as the ETBF, and it could be extended to embrace, for example, multiple target species and/or multiple fishing locations per trip.

As it is currently formulated, the dynamic state variable model assumes that fishers have perfect information, optimize their decisions in a longer-term (seasonal) context as opposed to having a shorter-term, more myopic view 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 the true differences under optimal decision-making. While it is clearly unrealistic to assume instantaneous and perfect adaptation to new circumstances, and the question of fisher's location choice decision time-frames is uncertain, the advantage of these assumption is that the model may 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 maximize profit.

The use of errors in stabilizing the dynamic programming equation appears to enable efficient model convergence without overt smearing of optimal fleet behaviour, so that there is high potential for this framework to be extended to address questions of increasing complexity. The approach has the advantage of being a technically simple means to encapsulate relatively complex dynamics, providing the state variable and state space and dynamic programming equation are sensibly defined. A large suite of future applications exist to which this approach may be applied. Even so, the simplified model framework developed here has enabled us to evaluate the feasibility of this novel approach to simulating longline fleet dynamics and to examine spatial effort allocations with respect to fleet competition and stock movement, opportunity cost and a simple spatial closure.

When multiple vessel types compete across different ports, the cell with the highest density of fish is still predicted to receive the most effort, but

the spatial effort pattern becomes influenced by the vessel capacity parameters. Port location affected the predicted fishing location choice only for the lowest capacity vessels. This is consistent with the ETBF in that the high-capacity vessels operating out of Mooloolaba (southern Queensland, and approximately the geographical centre of the fishery) show far less localization and greater range and hence a greater ability to track stock abundance irrespective of port location, than the lower-capacity vessels operating from New South Wales (the southern end of the fishery) and Cairns (the northern end of the fishery) (Campbell 2007). However, with greater time penalties associated with distance travelled, penalties on cost per unit travel and/or more extreme locations of high stock density, the effect of port location is likely to become more important.

With the imposition of fish movement onto the regime of competing vessel types and ports, the fleet generally tracked the central high fish density location throughout the season. However, the scenario demonstrates that, in general, lower-capacity vessel types are unable to effectively target the highest fish density location when this was further offshore, and as such, their optimal profit locations were consistently inshore of the highest fish density location. Conversely, higher-capacity vessel types are highly efficient in targeting the highest fish density irrespective of its location.

The greatest strength of the SDP approach over a statistical modelling approach is its ability to acknowledge opportunity cost, which enables us to estimate, outside of the data, fleet responses to both spatial management changes and other controls on catch and effort. The examples presented here clearly 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 maximizing their overall profit level. This is particularly apparent for the lowest capacity vessel type, which, when forced to fish almost continuously, rarely travelled to the areas of peak fish density. It is emphasized that the model does not render this outcome a foregone conclusion, because the range afforded to the lower-capacity vessels permits them to travel to the area of peak fish abundance at all times. When granted more flexibility in the choice of when the effort quota was spent, the incidence of trips to the areas of peak fish density increased, despite there being no marked change in trip duration. Similarly, restrictions on where vessels can fish also alter vessel behaviour. By considering future as well as immediate profit for a given level of remaining quota at a given time in the season, the stochastic dynamic approach 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. 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, as shown in the example presented.

The simple example presented here of a spatial closure of an area of sometime peak fish density demonstrates how predictions of effort redistribution by vessels differ from predictions that would be made using a statistical model of vessel location choice. Rather than the proportional increase in effort in the remaining areas that would be predicted by statistical models, the results here were consistent with Goni's (2006) observation of a concentration of fishers along the edges of the reserve. In statistical models such as multinomial logit models, probabilities for each individual vessel type and port redistribute in direct proportions if a particular location is removed. Effort that had previously occurred in the closed area now was mostly relocated to adjacent spatial cells and this occurred even when the peak fish density was not located in the closed area. Effort redistribution was also disproportionate among the spatial cells adjacent to the closed area, with preference given more to inshore than offshore adjacent areas. The overall profit level was not compromised by the closure, which would not have been the case had the effort been redistributed proportionately among the remaining areas. While these results follow intuitively for a model driven by profit maximization, and where fish distribution radiates evenly from a central peak density, the example nonetheless clearly illustrates the difference in modelled fleet response that was predicted by a mechanistic dynamic state variable model.

With the increasing emergence of spatial management as a tool to integrate biodiversity conservation, resource extraction and recreational use (Crowder *et al.* 2006), it is essential to have a method for predicting and evaluating behavioural responses of fishing fleets. Models for vessel location choice based on SDP force us to understand the factors driving the behaviour of the fleet and they provide a potentially more advantageous tool than

statistical models by which to evaluate the cost of closures and other types of spatial management for managing target species and environmental impacts to bycatch and habitat. The approach of state-based modelling may be used more generally in resource management where there is a need to predict and understand the redistribution of activities after closures, the introduction of protected areas and/or the implementation of other spatial effort controls.

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