Near real-time spatial management based on habitat predictions for a longline bycatch species

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SEDAR58-RD34

6 March 2019

Fisheries Management and Ecology, 2006, **13**, 365–380

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Abstract Southern bluefin tuna (SBT), *Thunnus maccoyii* (Castelnau), is a quota-managed species that makes annual winter migrations to the Tasman Sea off south-eastern Australia. During this period it interacts with a year-round tropical tuna longline fishery (Eastern Tuna and Billfish Fishery, ETBF). ETBF managers seek to minimise the bycatch of SBT by commercial ETBF longline fishers with limited or no SBT quota through spatial restrictions. Access to areas where SBT are believed to be present is restricted to fishers holding SBT quota. A temperature-based SBT habitat model was developed to provide managers with an estimate of tuna distribution upon which to base their decisions about placement of management boundaries. Adult SBT temperature preferences were determined using pop-up satellite archival tags. The near real-time predicted location of SBT was determined by matching temperature preferences to satellite sea surface temperature data and vertical temperature data from an oceanographic model. Regular reports detailing the location of temperature-based SBT habitat were produced during the period of the ETBF fishing season when interactions with SBT occur. The SBT habitat model included: (i) predictions based on the current vertical structure of the ocean; (ii) seasonally adjusted temperature preference data for the 60 calendar days centred on the prediction date; and (iii) development of a temperature-based SBT habitat climatology that allowed visualisation of the expected change in the distribution of the SBT habitat zones throughout the season. At the conclusion of the fishing season an automated method for placing management boundaries was compared with the subjective approach used by managers. Applying this automated procedure to the habitat predictions enabled an investigation of the effects of setting management boundaries using old data and updating management boundaries infrequently. Direct comparison with the management boundaries allowed an evaluation of the efficiency and biases produced by this aspect of the fishery management process. Near real-time fishery management continues to be a realistic prospect that new scientific approaches using novel tools can support and advance.

KEYWORDS: eastern Australia, habitat preference, satellite archival tags, southern bluefin tuna, spatial management.

Introduction

Increasing pressure on marine living resources has seen unsustainable levels of harvest in fisheries throughout the world (Hilborn, Branch, Ernst, Magnusson, Minte-Vera, Scheuerell & Valero 2003; Myers & Worm 2003; Pauly, Alder, Bennett, Christensen, Tyedmers & Watson 2003). Approximately 25% of the world's fisheries are over-exploited or depleted, and a further 44% are classified fully to heavily exploited (Garcia & Newton 1997; FAO 2004); a similar situation exists in Australia (Caton & McLoughlin 2004). Sound management relies on a number of approaches to reduce the risk of over-exploitation, or to aid the recovery of over-exploited fisheries (e.g. Walker 2005). One of the main tools has been catch limits, such as individual catch quotas, to prevent over-harvest of particular species (Smith & Smith 2001; Walker 2005). However, even the most well-intentioned fisher can exceed the quota when unwanted fish are captured during fishing operations targeting other species. Spatial management – of which Marine Protected Areas are a special case – is seen as an additional tool to assist recovery or prevent over-exploitation, and has been applied in benthic areas for some time (e.g. Hall 1998). Spatial management requires information on the habitat and

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movements of the species to be exploited or protected (Perry & Smith 1994; Williams & Bax 2001). In a number of countries, spatial management is seen as a way to reduce interactions with a variety of protected species, such as turtles and seabirds (Hyrenbach, Forney & Dayton 2000; Polovina, Kobayashi, Parker, Seki & Balzas 2000; Polovina, Balazs, Howell, Parker, Seki & Dutton 2004); however, the same approach can also be applied to minimise interactions with target and non-target fish species (Goodyear 1999). In pelagic longline fisheries, where targeting can be less precise, spatial management may be the best way to reduce unwanted interactions between fishing gear and species of concern. This spatial approach is, however, inherently difficult as ocean dynamics rather than fixed topography often govern residency and movement.

Southern bluefin tuna (SBT), *Thunnus maccoyii* (Castelnau), is seasonally distributed in the cooler waters of southern Australia (Caton 1991). A multinational convention, the Commission for the Conservation of Southern Bluefin Tuna (CCSBT), is charged with the sustainable management of the SBT resource (e.g. Polacheck 2002). One management tool is allocation of SBT quota to member nations. There is considerable international pressure to adhere to the allocated quota (Polacheck 2002). In Australia, the allocated quota is owned and traded between fishers, and at present is largely held by fishers involved in tuna farming around the Port Lincoln area in South Australia. SBT is purse-seined and towed back live to grow-out cages at Port Lincoln. However, this is not the only place in Australia where SBT are captured. The species is also seasonally present along the south-eastern seaboard of Australia, where it is incidentally captured in a major longline fishery (http://www.afma.gov.au/fisheries/tuna/etbf/default.htm). This fishery targets tropical tuna and billfish species and operates from a number of ports along the coast. The incidental capture of SBT by non-quota holders in this fishery threatens to violate Australia's adherence to the CCSBT quota, and is considered an important management issue.

Spatial management is the current method used to minimise the capture of SBT by non-quota holders on the east coast of Australia in the longline fishery. The Australian Fisheries Management Authority (AFMA) restricts access to some areas of the fishing grounds to reduce the risk of SBT capture by operators without SBT quota. In the 2004 fishery season, the fishing ground was divided into three zones of which two were restricted access areas; fishing inside one zone was restricted to vessels holding at least 4 t of SBT quota (core zone), while in a second zone (buffer zone) 500 kg of quota was required. In the third zone (open zone), no quota was required as the catch of SBT was expected to be negligible, although catch reporting was still required. These zones are updated throughout the fishing season as the distribution of SBT changes with seasonal changes in the local oceanography.

The scientific contribution to this management issue has been to provide near real-time identification of SBT habitat to assist in setting the zones. Determining the distribution of suitable habitat requires information on the habitat preference of the species, obtained from electronic tags, and information about the current distribution of the habitat, obtained through the interpretation of satellite-based observations of sea surface temperature (SST) and a near real-time ocean model. Electronic tags are providing new insight into the life of fishes, especially oceanic species with basin-scale movements (Arnold & Dewar 2001; Gunn & Block 2001; Itoh, Tsuji & Nitta 2003). Satellite tags in particular, have been used successfully to obtain movement and habitat use data for tunas, billfish and sharks (e.g. Block, Teo, Walli, Boustany, Stokesbury, Farwell, Weng, Dewar & Williams 2005; Domeier, Kiefer, Nasby-Lucas, Wagschal & O'Brien 2005). The definition of habitat for pelagic species is complex, however; fish distribution generally depends on both biotic (e.g. prey distribution) and abiotic (e.g. temperature) characteristics. In this paper, habitat is defined on the basis of temperature preferences, but it is acknowledged that more complete habitat descriptions will emerge in future.

This paper describes the use of a habitat prediction model to support fisheries management. The framework presented here has been continuously improved since AFMA fisheries managers first applied a spatial management approach in 2000 and has progressed from interpretation of single SST images and expert understanding (J. Gunn, personal communication) to prediction based on SST preferences (Hobday & Gunn 2004), to the current model presented in this paper. The current approach supports near real-time spatial management through the development of a vertically resolved, temperature-based SBT habitat model that incorporates spatial and temporal variability. This habitat model and oceanographic data are combined to develop a near real-time indication of the probability of SBT occurring in different areas off the east coast of Australia. Probability-based scenarios are then applied to the habitat predictions and managers place boundaries to divide the fishing ground into three management zones. These management zones are changed regularly throughout the fishing season to reflect changes in SBT habitat distribution. A comparison

of the placement of the boundaries by real managers to hypothetical boundaries placed by a computer algorithm is also presented, together with an investigation of the effect of: (i) using outdated predictions; and (ii) update frequency on the performance of the management zone approach for SBT.

Methods

Temperature preference of SBT

Information on the temperature and depth preferences of adult SBT (the principal age classes caught in the ETBF) in the region of the ETBF fishery were gathered using pop-up archival tags (PATs) (J. Gunn and T. Patterson, unpublished data). PATs are externally attached to SBT and deployed for a predetermined period (up to 12 months). Each PAT has a temperature, depth and light sensor. At the end of the deployment period, a pin is corroded and the tag detaches from the fish. Once at the surface, data are retrieved using the Argos satellite system. The amount of data a PAT can transmit is limited by its battery capacity which in turn is limited by the physical size of the tag. Consequently, only a summary of the data is returned. This summary is transmitted in the form of temperature depth profiles and frequency distributions of temperature and depth. These data summarise fish activity over pre-specified intervals of between 4 and 12 h depending on the deployment period of the tag.

The temperature preference of SBT for management support in 2004 was determined from data obtained from 18 recovered PATs; six recovered in 2001, two in 2002, seven in 2003 and three in 2004. The 18 tags covered 769 days of potential information. Individual tags contribute between three (0.39%) and 181 (23.5%) days of data. Longer record periods (e.g. data summarised every 8 h instead of every 4 h) were used for tags with longer intended deployment times, consequently the proportion of total data records attributed to an individual tag is less dominated by single fish than expected – between 0.56% and 17.7% of records come from a single fish. These SBT tags covered the area of interest for the ETBF (Fig. 1).

As the behaviour of SBT, and thus the habitat preference, is believed to change throughout the year (J. Gunn & T. Patterson, unpublished data), it was considered important to include only data from a similar time of year to the model prediction date. This is based on the assumption that intra-annual variation in habitat preference is greater than inter-annual variation. This assumption is made for a variety of

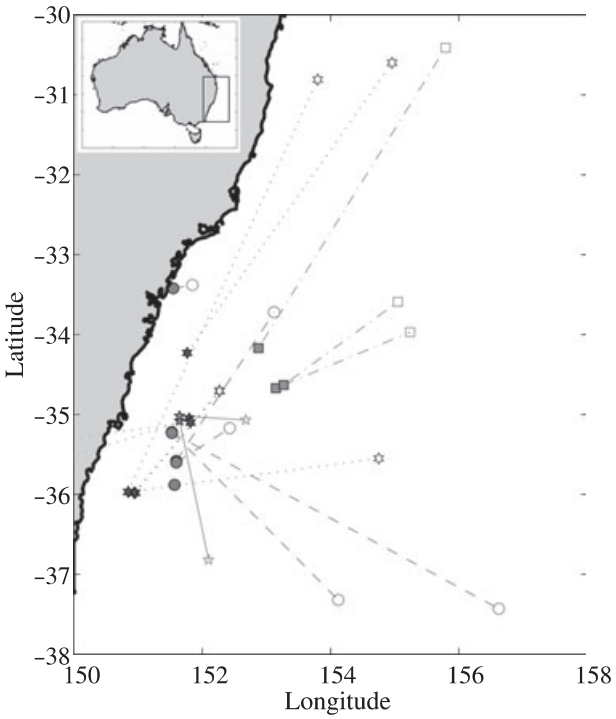

Figure 1. Southern bluefin tuna pop-up archival tag deployment and pop-up positions for 18 tags released off the east coast of Australia (2001–2004). Filled markers indicate the deployment position and marker outlines indicate the pop-up positions: circles (2001), stars (2002), asterisks (2003) and squares (2004).

oceanographic analyses, and the resulting signal over the course of a year is referred to as a climatology. The use of a restricted portion of the habitat preference climatology presents a compromise between using enough data and choosing data from a time that is representative of the analysis date. For the analyses presented here, unless stated otherwise, all data within 30 calendar days of the analysis date were used for habitat predictions. This window of 60 days was chosen as it was the smallest time range for which a reasonable amount of data remains available for the analysis, and reflects the temporal scale over which tuna migration (an indication of a change in habitat preference) occurs.

Calibration of temperature data from tags

The SBT habitat preferences were based on SST data extracted from PATs. The preferences were then applied to satellite-based SST observations and subsurface model temperatures. It is important to verify that there is no systematic difference between tag and satellite temperatures. The tags continue to gather and transmit SST data after they have detached from the

fish and are floating at the surface; at the same time good position estimates from the Argos satellite system are available. In total, 690 SST transmissions over 185 different days were available from tag deployments. Statistical analysis revealed that the SST reported by the tag is 0.76 °C (95% CI is between 0.49 and 1.03 °C) warmer than the satellite-based SST observation for the same position. This correction was applied to the habitat preferences (Hobday & Hartmann 2005). Unfortunately, sub-surface temperatures were only available while the tag was attached to the fish and there was too much uncertainty in the position of the fish during this time to allow comparison to the corresponding sub-surface model data. The only time when both a good position estimate and a sub-surface temperature profile from the tag were available was just after release and just prior to the tag popping to the surface. The number of SBT tags available was insufficient for calibration of sub-surface temperatures at this time.

Oceanographic model

Information about the near real-time temperature of the water column at a particular date and location is obtained using satellite images and an oceanographic model. The satellite images provide SST at each gridpoint (location) in the region of interest and the oceanographic model provides sub-surface temperatures. The Bluelink oceanographic model incorporates near real-time satellite altimeter and SST data, and in combination with a vertical climatology for the Australian region, resolves vertical ocean structure at 43 standard depths (0:10:70 75 80:10:110 125:25:300 350:50:1000 1100:100:1600 1750 2000). The grid scale of the model is 5 km in the horizontal dimension (http://www.marine.csiro.au/bluelink/). This oceanographic model is considered an experimental product and will be subjected to continued validation and improvement; as such its accuracy remains uncertain (D. Griffin, personal communication). Unfortunately, with the cancellation of a wide-swath altimeter due for launch in 2008 and the future demise of present satellite-based altimeters the data required by the sub-surface model will degenerate in coming years. Consequently, the habitat model output will decrease in quality unless other oceanographic models under development provide significant improvements that compensate for the poorer observational data. For the purposes of this study and the analyses presented, the oceanographic model was assumed to represent the vertical water structure adequately.

Depth-integrated analysis (3D habitat model)

The east coast longline fishing fleet generally operates in the northern (and warmer) side of the area under SBT spatial management. The management aim was therefore to restrict fishing vessels without quota to a warmer area than where SBT occurs. To produce the habitat prediction for a particular date, the corresponding oceanographic model and satellite data were extracted. For each grid point on the extracted data set (latitude, longitude and depth) the proportions of temperature observations from the PATs cooler than the temperature from the oceanographic model/satellite data were recorded. These proportions were then averaged throughout the water column at each location to produce an indication of how warm the water column was in comparison with SBT temperature preferences.

The statistic derived from this process is a cumulative probability distribution of SBT presence as a function of increasing water temperature. Management can use these data by ensuring that operators without quota can only access water with values higher than a particular value of this statistic. For example, if a fishing vessel is only allowed to fish in areas that have a value greater than 0.95 for this statistic then it will be fishing an area where SBT are predicted to spend less than 5% of their time.

Temperature analysis at a single depth

A formal framework for comparing the temperatures observed by tags and those obtained from the oceanographic model or satellite observations of SST is presented here. The suitability of water temperature at a particular location, time and depth was calculated first. For the sub-surface analyses it was necessary to interpolate the tag temperature-depth profiles to match the depths specified in the oceanographic model; full details of this procedure are provided in Hobday & Hartmann (2005).

The observations from each tag were given equal weighting and pooled. The temperature and proportion of time spent at depth d for the kth observation were denoted by t_{kd} and p_{kd} respectively. The number of available observations was denoted by K. For depth d, the proportion of tag temperatures cooler than the temperature obtained from the oceanographic product (o_d) was given by:

$$S_d = \sum_{t_{kd} < o_d} \beta_k \text{ where } \beta_1 = \beta_2 = \cdots = \beta_{k-1} = \beta_k = 1/k.$$

With this formulation each observation is treated equally. In future, it might be appropriate to weight observations by the proportion of time the fish spent at that depth during that time period. For example, if a fish avoided a particular depth because of water with an unfavourable temperature or frequented a depth of favourable temperature then weighting might be appropriate.

Water column analysis

The statistic (s_d) calculated in the previous section (the proportion of time SBT spend in water cooler than at some point) was for a particular location and depth. To obtain a statistic ($\hat{s}$) for the entire water column at some location, the previously calculated s_d needs to be combined over all available depths:

$$\hat{s} = \sum_d w_d s_d, \quad \text{where } w_d \text{ are weights and } \sum_d w_d = 1.$$

The statistic $\hat{s}$ can be interpreted as the proportion of time SBT spend in a water column 'cooler' than at this location. This raises the question of what importance to assign to each depth (w_d). Taking a simple mean over all depths is an arbitrary approach as it would give equal importance to all depth layers in the oceanographic data set. These depth layers are irregularly spaced according to oceanographic convention, thus the mean would be biased towards depth ranges with finer spacing; the habitat model should produce results independent of the depth spacing in the oceanographic data set.

Ideally, each depth layer should be weighted by the magnitude of the effect that the temperature in that layer has on tuna presence/absence. In the absence of any other information, the assumption was made that the importance of a particular depth layer was directly proportional to the amount of time fish spent in that layer over all available records. Under this assumption the weightings are:

$$w_d = \frac{\sum_k p_{kd}}{\sum_\delta \sum_k p_{k\delta}} = \frac{\sum_k p_{kd}}{k}.$$

The maximum depth for the habitat analysis was set at 200 m. This limit was chosen because it covers all depths in which the fishery gear operates (in the PAT data set SBT spent 92% of their time in the top 200 m).

Habitat preference scenarios

The statistic produced in the previous section ($\hat{s}$) is the cumulative probability distribution of SBT presence as a function of increasing water column temperature. Management should aim to ensure that operators with no or minimal quota can only access areas that have a high value for this statistic (and consequently a low probability of SBT presence). However, this is can be a difficult task – how high a value is high enough? Also, how should the complex boundaries produced by the analysis be handled? Any management boundaries imposed need to be simple to understand and communicate to operators on the water and thus minimise compliance monitoring.

The former problem – what statistic value to choose as a cut-off – was handled through consultation with management, although ultimately it should be based on a more scientific basis that aims to restrict expected bycatch in each of the previously discussed zones to acceptable levels: the lowest 80% ($\hat{s} < 0.8$) was classified as core zone, the next 15% ($0.8 < \hat{s} \leq 0.95$) as the buffer zone and the final 5% ($\hat{s} > 0.95$) as the open zone. Other less conservative scenarios to reduce unwanted SBT catch (e.g. a 50%:35%:15% split) were considered in the past and rejected by management. The output provided to management showed the zone into which each area in the fishing ground was classified. The boundaries could be complicated and managers preferred boundaries between the zones comprising at most a four segment boundary running roughly west–east from the coast. In 2004, managers fitted these boundaries by eye after taking other factors into account (e.g. the positions of fishing harbours).

Automated placement of management boundaries

The analysis that produced the habitat predictions was relatively objective (apart from the choice of scenario to define zones), but the placement of the management boundaries was a subjective process. A process for automatically allocating management boundaries was developed that will in future reduce the potential for subjectivity from the boundary placement by managers, as well as guide placement in oceanographically complex situations. A range of boundary complexities was considered for automated boundary placement; however, because of the optimisation routine used, it was of no benefit to use boundaries exceeding three segments in complexity; this matched the level of complexity used by fishery managers in 2004.

Objective function choice

To enable automatic selection of best-fit management boundaries it was necessary to produce an objective function (f) that described how well a particular set of

management boundaries classifies the habitat. This function was based on minimising the area that the management boundaries misclassify. Thus, placement of boundaries was systematically varied until the misclassified area was at a minimum.

Given that each habitat point is in one of three categories, there are six possible types of misclassifications, and three correct classifications (Table 1). Those three categories below the diagonal in Table 1 contribute to precautionary management as habitat in which SBT catch is likely to be low but is still made inaccessible to the fishing fleet without quota, while the three categories above the diagonal contribute to non-precautionary management as habitat in which SBT is likely to be found and is made accessible to fishing boats with insufficient quota. Each misclassified area was weighted by the number of categories by which it was misclassified (Table 1). For example, core habitat from the analysis classified as open by management is two categories from the correct management classification, while buffer habitat allocated to the core zone by management was only one category from the correct classification. It is possible to introduce a desired bias towards precautionary or non-precautionary management by changing the weightings associated with these misclassifications. However, there is a more transparent means by which this can be achieved, which is discussed below.

Denoting Table 1 as a matrix C, the sum of those classification categories that result in non-precautionary management was denoted u, and those that resulted in precautionary management as l:

$$u = \sum_{i=1}^{2} \sum_{j=i+1}^{3} C_{ij} \text{ and } l = \sum_{i=2}^{3} \sum_{j=1}^{i-1} C_{ij}, \text{ where } C_{ij} = |i - j|.$$

A simple objective function, f, could sum u and l; however, to keep the contribution to f from both misclassifications similar (to reduce bias toward either side) a term was added to the objective function that is the difference between the two components: $f = u + l + k|u - l|$. The multiplier k (≥ 0) can be adjusted to weight the importance of keeping the difference between the two components ($u - l$) low relative to keeping their combined total ($u + l$) low. If k is set to 0, no effort is made to reduce the bias; as k is increased the amount of potential bias is decreased. By introducing this factor, a trade-off is made; more pixels may be misclassified overall to minimise the bias. Additionally, if it is desirable to introduce a systematic bias towards precautionary or non-precautionary management a factor w (≥ 0) can be introduced:

$$f = u + l + k|u - wl|.$$

For $w > 1$, the bias is towards non-precautionary management, whereas if $w < 1$ the bias is towards precautionary management. For example, if $w = 2$, to minimise the term $|u - wl|$ then $u = 2l$; this would result in twice as much area being managed in a non-precautionary manner (u) than in a precautionary manner (l). This would result in bias towards non-precautionary management. In this analysis, $k = 1$ and $w = 1$; these values were chosen to achieve unbiased management boundaries.

Optimiser algorithm for automatic boundaries

The optimisation algorithm used to fit management boundaries automatically to the SBT habitat areas was the Nelder–Mead simplex method as implemented in Matlab R14 (*fminsearch*) (The Mathworks, http://www.mathworks.com). To prevent the two management boundaries from crossing it was necessary to introduce a penalty function as the minimisation routine does not permit the specification of constraints. The presence of this penalty function and the existence of many local minima resulted in the global minimum generally not being located (especially for more complex boundaries). This was evident from the strong dependence of the solution on the initial starting point provided to *fminsearch* (*fminsearch* requires an initial solution which it then perturbs).

Table 1. Habitat (mis)classification categories that can occur during placement of management boundaries

	Actual classification from temperature-based habitat model		
Managed as	Open	Buffer	Core
Open	Correct management (0)	Non-precautionary management (1)	Non-precautionary management (2)
Buffer	Precautionary management (1)	Correct management (0)	Non-precautionary management (1)
Core	Precautionary management (2)	Precautionary management (1)	Correct management (0)

The relative effect of the (mis)classification on the objective function is indicated in brackets for each category, i.e. weightings used in the objective function.

Management decisions made using outdated information

The automatic boundary allocation analysis described above also allowed examination of the consequence of setting management boundaries using outdated habitat predictions (i.e. the effect of delaying management decisions). By necessity, the habitat prediction reports supplied to the fishery managers and used for deciding on management boundaries were outdated by the time management decisions were made. An initial 4-day delay was because of the oceanographic model upon which this habitat model was based. At times, problems in the system producing the oceanographic model output occurred, resulting in further delays. Issues ranged from problems receiving the satellite data to problems running the model, and these usually took 1 or 2 days to resolve. As a result, the 2004 habitat prediction reports delivered to managers relied on oceanographic model output that was 4–6 days old.

Once the report was electronically delivered to the fishery managers there were additional delays for logistical reasons. An understanding of the practical effect on the habitat classifications as a result of delayed management decisions was therefore of great importance. The effect of using outdated predictions was found by calculating the objective score, and the misclassified area obtained, when management boundaries produced for older analyses were applied to the more recent analyses. This retrospective analysis procedure was carried out throughout the 2004 period using data of different ages. The increase in the objective function obtained for each day when using data of a certain age showed the effect of managing using outdated predictions.

SBT habitat climatology

To inform management and stakeholders about likely changes in the distribution of SBT habitat and to compare the distribution of the current habitat prediction with the typical distribution of SBT habitat at that time of year, an SBT habitat climatology was formed. This was produced by analysing the satellite SST data from 1993 onwards and recording the position of the buffer zone each day. For this analysis only, the buffer zone was defined by two latitudinal boundaries placed such that only 5% of the buffer zone was north and south of these boundaries respectively. These habitat zone climatologies were used to compare the present situation with historical averages and extremes to provide an indication of what changes can be expected over the year.

There were two major limitations with this habitat climatology analysis that necessitated the use of an SST-only model. The oceanographic model that provided temperature at depth was only available from the start of 2004, consequently only SST could be used to generate a multi-year climatology (1993–2004). As a result of the change in data availability throughout the year, no restriction on the dates of SBT PAT data included in the climatology analysis were made. In future, a climatology based on the depth-integrated model will be possible.

Results

The development of the model and the individual steps that are undertaken for each analysis are best illustrated by presenting a series of examples, in this case for 6 August 2004. This date was chosen arbitrarily from those dates corresponding to management decisions in 2004. Figure 2 shows the cumulative probability of SBT presence as a function of increasing temperature. The processing of the SST images used in the analysis attempts to detect cloud cover and returns missing values in those areas where cloud cover prevents reliable SST estimates. In those areas where no SST values were returned, the habitat suitability analysis was based entirely on sub-surface model output. The same analysis conducted on each depth layer individually showed how the habitat suitability changes through the water column (Fig. 2). Particularly noticeable was a north–south line just off the coast that shows that sub-surface water was less suitable than the surface water and the eddy at 37° S. The result for the full water column was obtained when the individual depth layers were combined (Fig. 3a). The management zones previously defined were then applied to produce the figure that was delivered to management (Fig. 3b).

Two-tailed analysis and model validation

The methods explained how to derive the habitat suitability of a particular location by examining the cumulative probability of SBT presence. Cumulative probability was used as the ETBF fishery operates in the northern waters along the east Australia coast (which are generally warmer) and management zones the waters from north to south. Alternatively, the water masses in which SBT presence was most likely could be identified and these water masses excluded from the fishery. This approach could be conducted using the results from the previous analysis, as outlined below.

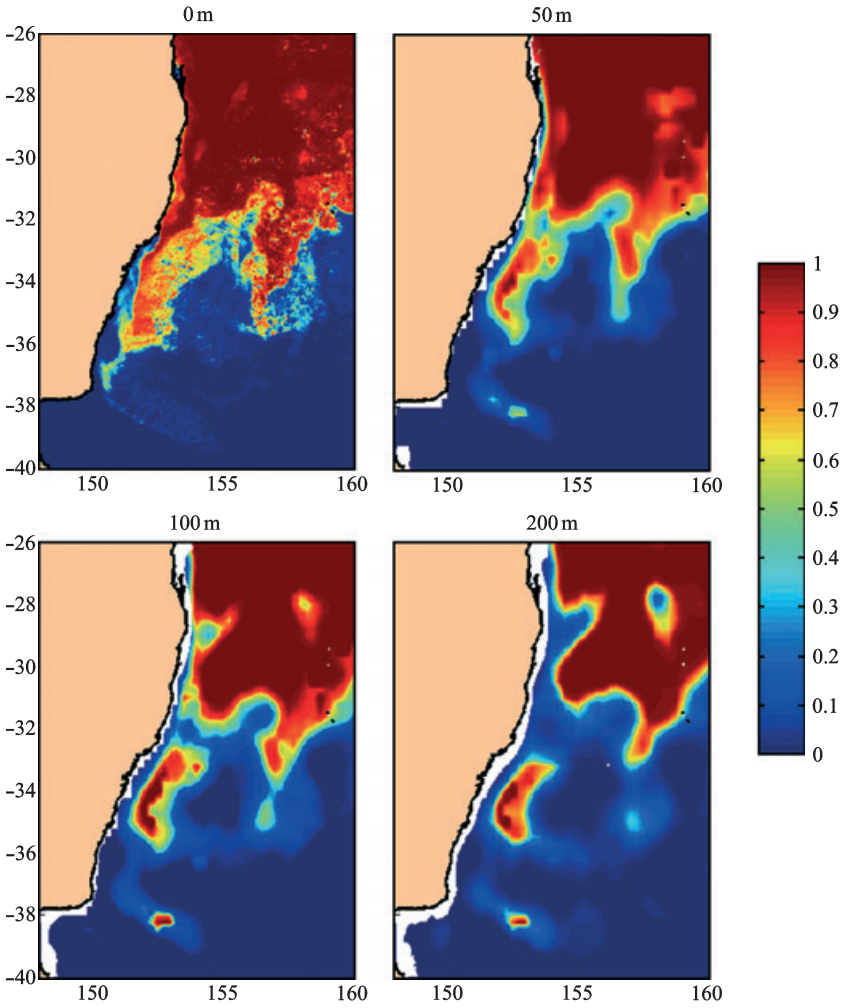

Figure 2. Analysis of southern bluefin tuna (SBT) habitat suitability at four example depths (surface, 50, 100 and 200 m) for 6 August 2004. The colour indicates the proportion of time SBT spent in water colder than that at a particular point.

The cumulative probabilities $\hat{s}$ were converted to two-tailed cumulative probabilities:

$$\tilde{s} = |2\hat{s} - 1|,$$

such that the water mass containing all values $\tilde{s}$ less than some value x should contain a proportion, x of the SBT in the total area. Figure 4 shows the values of $\tilde{s}$ for the same time period depicted in Figure 3. A test of validity of this two-tailed prediction, and hence the habitat model was performed using SBT catch data from the longline fishery. When the values of $\tilde{s}$ were calculated for locations and dates where SBT were caught, these values should have a uniform distribution between 0 and 1. This assumed that the fishing effort randomly sampled water of all temperatures that were experienced by SBT in the data set. This assumption was probably not met (because of differing availability of different temperature water and selective targeting by fishing vessels), but nonetheless a probability plot (Fig. 5) for longline sets in which SBT were caught showed that $\tilde{s}$ had a relatively uniform distribution, as expected if the model generated realistic habitat preferences. Note in Figure 5 that when all longline sets were included in the analysis (regardless of whether SBT where caught) $\tilde{s}$ did not show a uniform distribution, indicating that the predictions produced were specific to SBT.

SBT habitat climatology

The SBT habitat climatology generated with each habitat prediction allowed a comparison between the distribution of the current habitat prediction with the typical distribution of SBT habitat at that time of year

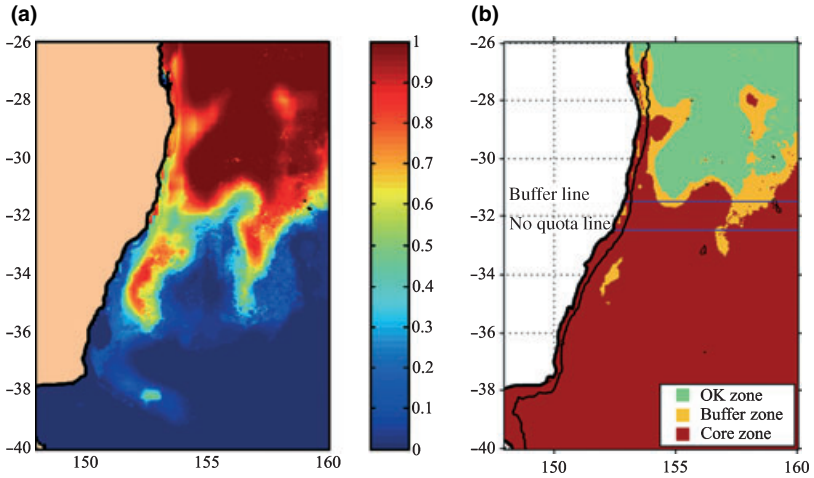

Figure 3. (a) Depth-integrated analysis of southern bluefin tuna habitat suitability for 6 August 2004. The colour value indicates the probability of tuna being in water that is generally colder than that found throughout the water column at a particular location. (b) Habitat management zones for 6 August 2004 using 0.8 and 0.95 probability cut-offs for the buffer and core zone respectively. Example management lines are indicated.

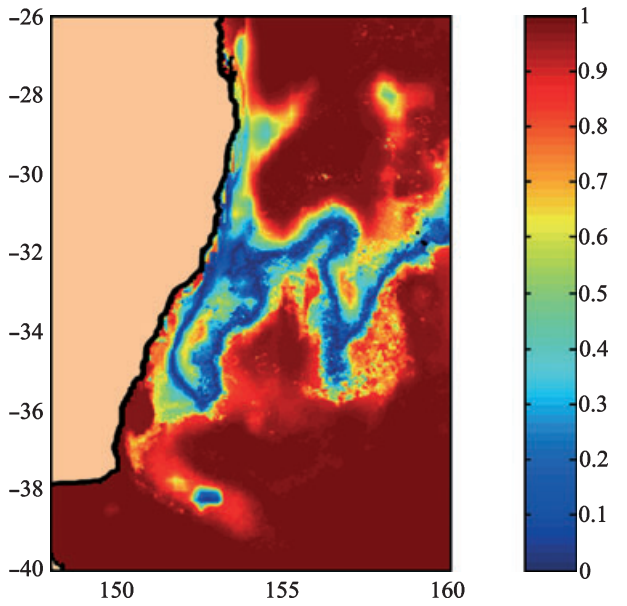

Figure 4. Two-tailed southern bluefin tuna (SBT) habitat probability distribution. By including all pixels coloured less than a particular value in an area, a confidence limit on SBT catches equivalent to that value is formed. For example, 95% of SBT catches are expected to occur in the waters corresponding to the colours less than 0.95 on this scale.

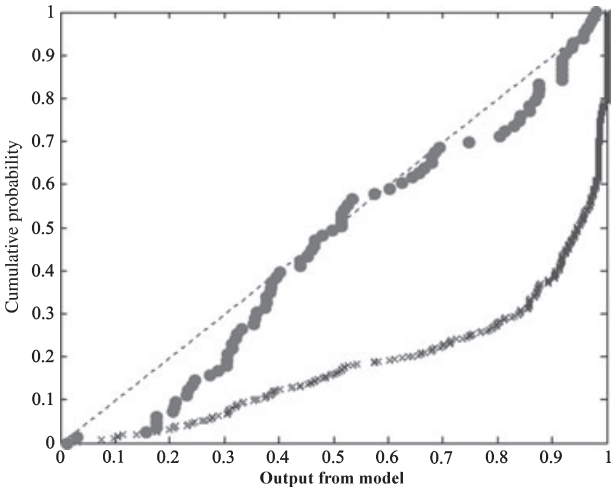

Figure 5. The cumulative probability of obtaining model output scores for all ETBF longline sets from 2001 to 2004 (crosses) and for those longline sets on which southern bluefin tuna were caught (circles). This probability plot is analogous to a quantile–quantile (QQ) plot. The data used to produce this figure were obtained from the AFMA observer logbook database version held at CSIRO Marine and Atmospheric Research.

(Fig. 6) and informed management and stakeholders about likely changes in the distribution of SBT habitat over the year. These illustrations were distributed to stakeholders to show the likely management restrictions that may occur through the fishing season, and are now considered an important stakeholder communication tool (http://www.afma.gov.au/fisheries/tuna/etbf/notices/default.htm).

Placement of management boundaries

The location of the SBT management boundaries during the 2004 season was changed regularly by the longline fishery managers in response to predictions of the temperature-based habitat model. Boundaries were placed to best match the east–west extent of the habitat zones from the habitat scenario. A northern boundary specified the start of the buffer zone; only vessels with SBT quota in excess of 500 kg could fish

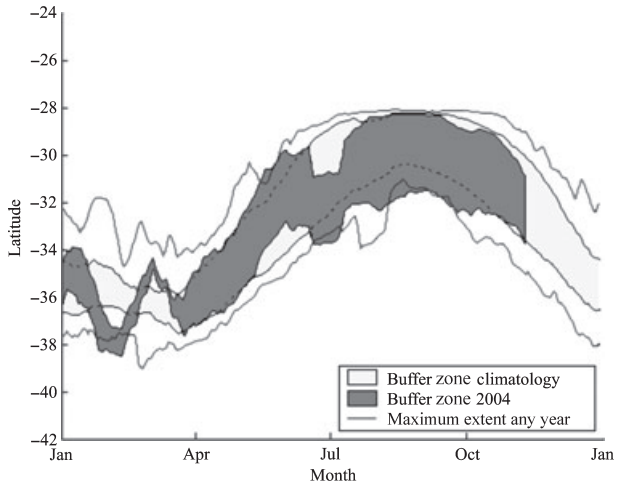

Figure 6. Southern bluefin tuna buffer zone climatology derived using SST data from 1993 to 2004. The northern and southern boundary of the buffer zone in the current year, and the maximum/minimum latitude of the buffer zone in any year are also shown. To produce this climatology it was necessary to relax the date restriction condition and use the SST-only approach. Additional details provided in the text.

south of this boundary. The southern boundary specified the start of the core zone; only vessels with quota in excess of 4 t could fish south of this boundary. Boundary placement was by inspection of the figures, not by algorithm.

In the 2004 season (June to November), fishery managers made a total of seven boundary placements. A selection of boundaries is shown in Figure 7 along with the habitat model output upon which they were based. These varied from simple boundaries running east–west (e.g. 4 June, Fig. 7), to more complex boundaries comprising several segments (e.g. 12 July, Fig. 7). No boundary had more than three segments. These management boundaries approximate the edges of the core and buffer zones but do not capture the full complexity of the habitat shape.

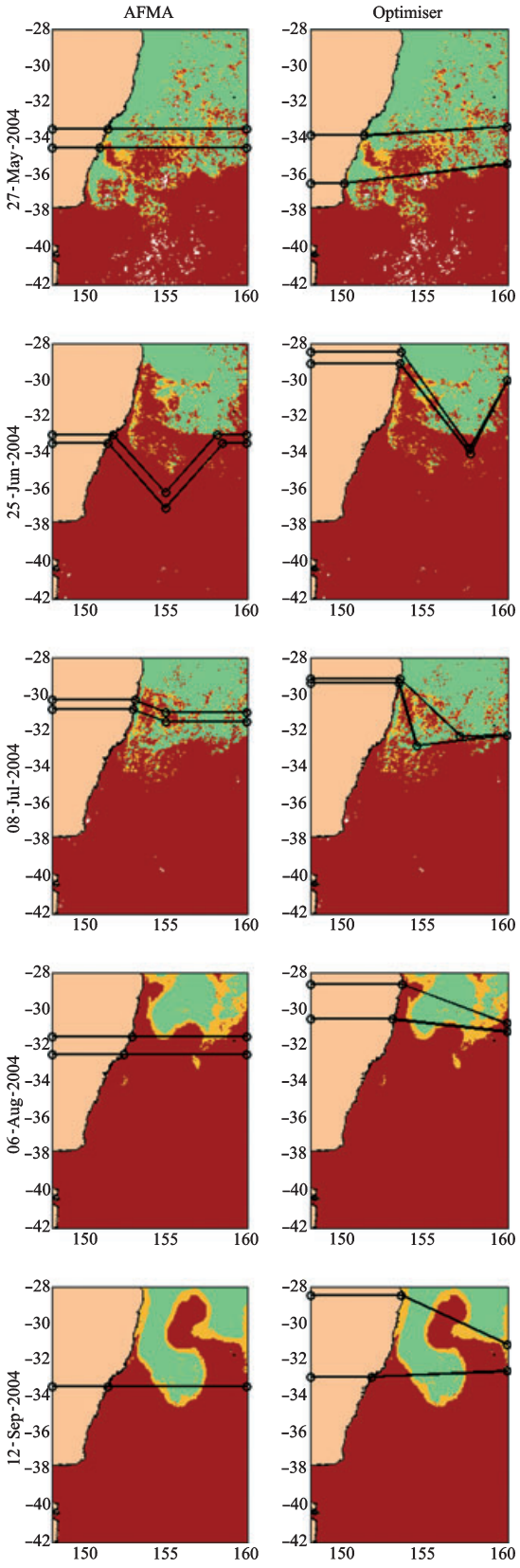

Figure 7. Examples of actual management boundaries placed by fishery managers (AFMA) (left panels) and those calculated using the optimiser algorithm (right panels) for the 2004 season. These boundaries are overlaid on the habitat zone images on which both were based. The upper line divides the open zone from the buffer zone, while the lower line divides the buffer zone from the core zone. Management decisions early in the season were based on the output from an earlier analysis method, the output of which is shown here to provide a comparison with the automated boundary placement method. This earlier analysis was more susceptible to surface cloud contamination as is apparent on the first three panels where it was used. In one case, management chose to place only one boundary (12 September 2004).

Automated placement of boundaries: comparing management decisions

The management boundaries automatically placed by the optimising algorithm were compared with those chosen subjectively by the fishery managers. To conduct this comparison, the same images with which the management boundaries were chosen were subjected to the optimiser. The optimiser was allowed to construct boundaries that were equally complex. Figure 7 shows the boundaries that were determined by managers and those produced by the optimiser, while Figure 8 compares the management outcome achieved with these approaches.

The optimiser management boundaries always improved upon the management-placed boundaries (AFMA) when the objective function values were compared. However, at times (27 May and 12 September) the AFMA boundaries classified a larger proportion of the area correctly (Fig. 8), but this was at the expense of biasing the management in a precautionary or non-precautionary direction (and therefore a worse solution according to the objective function). For example, on 27 May, AFMA management boundaries classified more pixels correctly, but the boundaries were biased towards precautionary management (Fig. 8). The solution produced by the optimiser algorithm for the same model output date classified more pixels incorrectly, but incorrectly classified an equal number of pixels in both categories. On the remaining 5 days, the algorithm classified more pixels correctly and did so in an unbiased manner (i.e. the area managed in a precautionary manner was the same as the area managed in a non-precautionary manner). Note that five of the AFMA boundary placements showed a bias towards non-precautionary management, and only two (27 May and 8 July) were biased towards precautionary management (Fig. 8).

Delays in allocating management boundaries

There were several causes of data delays that resulted in outdated habitat information. The oceanographic model produced data that were about 4 days old and there were also delays of between 0 and 8 days from the delivery of the habitat prediction report to the date when management boundaries were changed. Thus, managers in 2004 used model output that was between 4 and 12 days old at the time of the management decision. Once a boundary was placed by management, it remained for between 11 and 37 days before being updated. Habitat predictions were delivered every 14 days; but, when the habitat zones were static, no changes to spatial management rules were needed.

Figure 9 shows the increase in misclassified area as a function of the age of the data used for setting management boundaries; this shows, for example, that for 5-day-old data there is an increase of approximately 30% misclassified area (misclassified area goes from 11% to 14%). The large confidence interval in

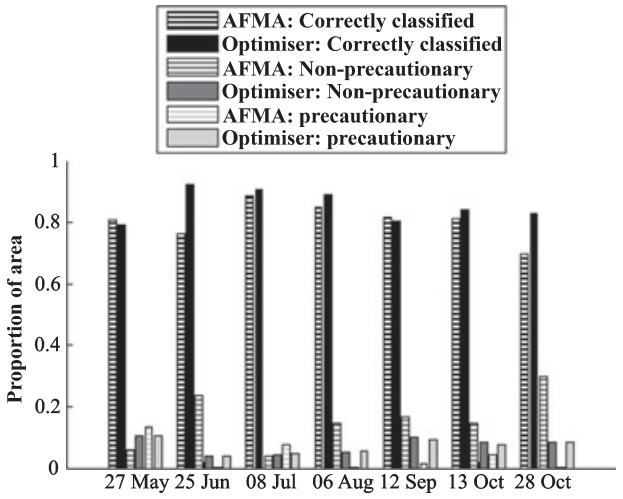

Figure 8. Comparison of the management boundaries allocated by fishery managers (AFMA) in 2004 and the corresponding placements made using the automated boundary allocation process (optimiser). The proportion of the area classified correctly, in non-precautionary, and in precautionary categories is shown on the *y*-axis. The date of model output used in allocating management boundaries is shown.

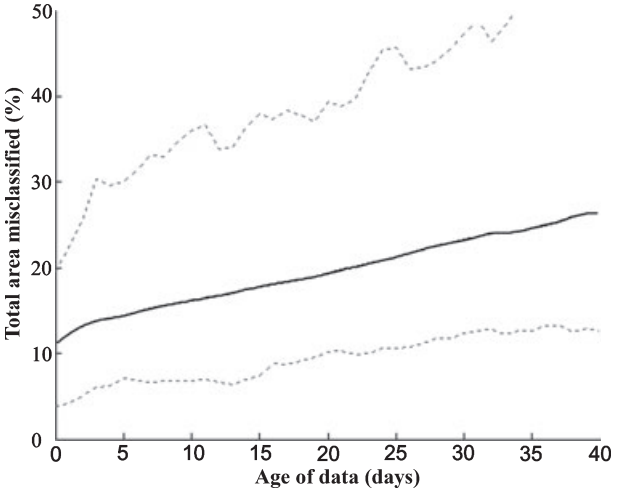

Figure 9. The increase in the proportion of the total area that was misclassified as a function of the age of the data used for the management decisions. The dotted lines indicate the 95% confidence interval. Management boundaries with two segments were used for this analysis.

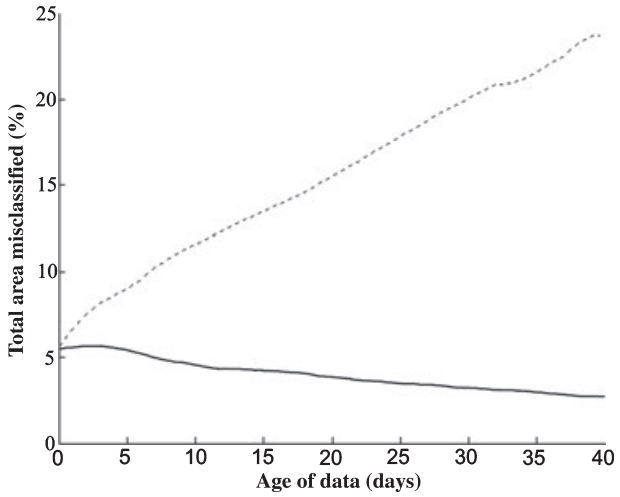

Figure 10. Decomposition of the misclassified area into the components contributing to precautionary (dotted line) and non-precautionary management (solid line) as a function of the age of the data used for the management decisions. Management boundaries with two segments were used.

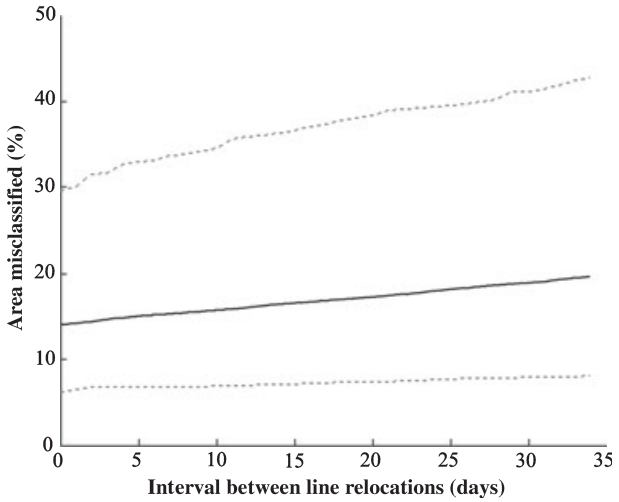

Figure 11. Increase in the proportion of the total area misclassified as the frequency of management boundary updates decreased; the dotted lines indicate the 95% confidence interval. The 0-day point is comparable with the 4-day mark in Figure 9 as the best data available for making management decisions was 4 days old.

Figure 9 (and subsequent figures) is because of the variable rate of habitat change throughout the season (see Fig. 6). For example, during August the rate of habitat movement south is lower than later in the season, and thus the effect of managing with outdated information is reduced. Later in the season, habitat is moving more rapidly and using old data can lead to greater misclassification. Averaging this pattern leads to a wider confidence interval.

The increase in the two misclassification components, u and l, that contribute to the objective function was investigated individually (Fig. 10). Different behaviour is exhibited by each component because during the period of management (July to November) core SBT habitat is contracting to the south. Consequently, the management boundaries using outdated predictions are 'left behind' to the north resulting in a precautionary bias.

Frequency of boundary updates by management

An important factor determining the efficiency of the management boundaries is the frequency with which they are updated. The more frequent the updates, the better management can respond to the rapid changes that can occur. There are, of course, practical limitations, including the need to communicate changes to the fishing fleet and permit the fleet the time to adjust to changes, such that a boat fishing the open zone does not find itself deep in core zone following an overnight zone reclassification.

The misclassified area increased as the interval between management updates increased (Fig. 11). For example, if boundaries were not moved for 10 days there was an average increase in the misclassified area of approximately 20%. This was based on the assumption that decisions are made using the best possible data; in this case experience has shown that 4-day-old data are attainable and this delay was used for this analysis. To put the potential changes in perspective, during the 2004 season the intervals between management boundary changes were 23, 11, 30, 37, 36 and 17 days. In future years, when more SBT model output is available, it will be possible to indicate the expected increase in misclassified area as a function of both the time of year and the age of the analysis used for management.

Discussion

The development of a real-time spatial management support tool for fisheries management has been a success; it has been adopted by the relevant Australian fishery managers and has helped reduce unwanted bycatch of SBT in cases where quota to land the species is in limited supply to fishers. This scientific support for management aims to underpin real-time adaptive management in a transparent and objective fashion. Such management is one way of increasing sustainability of marine fisheries, and in this case, also underpins a national commitment to an international management agreement. Additional outputs, such as

the habitat climatology, provided stakeholders with a better understanding of the scientific process and an appreciation of the value of near real-time spatial management approach in managing a complex issue.

This temperature-based habitat model has evolved over approximately 4 years, from an SST-only model to a depth-integrated model, and has become an important part of the management process in this Australian longline fishery. The increase in SBT temperature preference data from PAT tags over this time period has also allowed a restriction to habitat preferences close to the time considered. These improvements and a consultative period of development have led to stakeholder and management confidence in the approach. The visualisations and climatologies are also readily understood by the stakeholder group, which is an additional benefit. Providing management support tools that address these issues is a challenge for fisheries science, given the complexity of assumptions and models that underlie some analyses (Froese 2004).

Habitat characterisation

The pelagic habitat of SBT has been defined on vertical temperature preferences alone because these are the data obtained from both tags and output of the near real-time ocean model. As ocean models begin to describe other pelagic habitat characteristics effectively, such as productivity (e.g. Lehodey, Andre, Bertignac, Hampton, Stoens, Menkes, Memery & Grima 1998), at scales relevant to management, habitat prediction could be based on information gathered from other sources, such as catch distributions and more complicated habitat preferences (e.g. Bertrand, Josse, Bach, Gros & Dagorn 2002). These habitat characterisations have been a cornerstone of fisheries oceanography (e.g. Swartzman, Stuetzle, Kulman & Powojowski 1994; Bigelow, Boggs & He 1999), yet without information on the three-dimensional ocean structure, flexible spatial management options are harder to implement. Without the ocean models, habitat predictions and subsequent spatial management options would be restricted to static closures (e.g. Goodyear 1999), or surface identification of habitat features (e.g. Polovina *et al.* 2000; Zagaglia & Stech 2004).

Evidence for changes in local and regional oceanography are now emerging from ocean models and these changes are at scales relevant to local resource users. Habitat models can be used to demonstrate the range of changes in resource distribution that are likely under these scenarios. In combination with socio-economic elements, these models will support more comprehensive management approaches for enhancing ecological as well as economic sustainability. For example, changes in target species distribution as predicted by habitat models may allow foresight in the development of port facilities, or other regional development investment.

Future implementation and improvements

The increase in the misclassified area with delays in management decisions showed that every effort should be made to base decisions on the most recent data available, which, given the delayed nature of the oceanographic model output, will usually be around 4 days old. The increase in the misclassified area may result in an additional SBT bycatch and/or in an unnecessary closure of fishing grounds. In future, as the ocean model is further developed, this delay should be reduced and could eventually allow future ocean state predictions (D. Griffin, personal communication). Management may still choose to delay implementation of zones, to allow fishers a chance to vacate a now-closed area. already happened!

Improvement of the current SBT habitat model will also occur in future years. In particular, the estimated zones will be determined with greater confidence, as more SBT habitat preference data from PATs are collected and vertical water mass characterisation is improved. Against this background of biological model improvement is the expected loss of satellite platforms which will reduce the availability of data for oceanographic models. Changes in habitat preference as a function of fish size can be investigated, as can interannual variation in habitat preference. As tagging techniques are improved to allow deployments of increasing duration, it will become more probable that tuna will move out of the area of interest (the east coast). Thus, despite these deployments providing a wealth of new data it will become more important to ensure that the data incorporated into the analysis were collected while the fish was in the appropriate area. This will require effort in the area of geolocation which is currently of limited accuracy for PAT tags (J. Gunn and T. Patterson, unpublished data).

Additional validation of the model and method is important. For example, the expected reporting of SBT captures by observers aboard ETBF longline vessels in each of the three zones can be evaluated when a validated catch data set is collected. It might be expected that only 5% of longline sets would capture SBT or 5% of the CPUE would occur in the region that was defined as the most extreme 5% of the SBT

habitat. This use of probability levels for each zone also acknowledges that the predictions of where SBT will occur will not be possible with 100% certainty. In future the decision on probability levels should be made in combination with a calculation of the potential catch if that probability is realised. Such performance measures should be incorporated in this type of spatial management tool and will lead to improvements in the scenarios that underpin the management approach.

This habitat prediction approach allowed changes in management as SBT habitats moved in response to local oceanography. The importance of regular management boundary movements using the most recent analyses was demonstrated. Both fishers and managers have accepted the advantages of updating closure areas during the season to avoid SBT bycatch. Managers are committed to updating management boundaries as regularly as possible given the inherent practical limitations and ensure that decisions based on current analyses are obtained to assist in making these decisions. The automated boundary placement approach could be used to assist management in boundary placement in future, but, certain extensions need to be incorporated before the removal of the human element would be advocated. These include the ability of the optimiser to provide several different solutions that are (approximately) equal in their quality from the optimiser's perspective but may have different practical implications for the industry. The management boundaries to date have been allocated by managers and it is therefore necessary to provide a relatively simple classification of the survey area into the three different zones. However, even within these zones there are substantial differences in the likelihood of SBT presence. For example, the core zone includes habitats which range in expected suitability (e.g. 100% to 15%). The optimisation routine can easily handle the full detail of the analysis and an extension to use this might prove beneficial.

Near real-time spatial management

There are few examples of near real-time spatially explicit information provided to fishery managers to enhance sustainable fisheries and reduce unwanted species interactions. One other example is the rapid assessment of population composition based on genetic structure (Beacham, Lapointe, Candy, Miller & Withler 2004). In this case, the fishing effort allowed on salmon at particular locations is regulated according to the presence of particular stocks through a season. The turnaround time in providing management information was on the timescale of days (Beacham *et al.* 2004).

Habitat description to predict species distribution has been attempted for a variety of benthic and pelagic species (Brill 1994). For benthic species, where it is often the distribution of habitat features, such as bottom type that dictate distribution, habitat identification may not need to be updated provided that habitat damage has not occurred. Some benthic species, such as Atlantic cod, *Gadus morhua* L., show an interaction between temporally variable environmental features and consistent spatial features, such that habitat suitability at a point varies temporally (Perry & Smith 1994). Real-time habitat identification for these benthic species and most pelagic species is a challenge because the distribution of habitat is temporally variable. The availability of an ocean model for habitat prediction for SBT was considered important because these tuna are out of the surface layer for more than 60% of the time. Thus, subsurface structure was expected to play a large part in the habitat distribution. For species which spend a greater proportion of time at the surface, such as yellowfin tuna, *Thunnus albacares* Bonnaterre, a suitable habitat prediction model could be based only on real-time SST imagery, which is routinely available. Reliance on surface images does mean that cloud cover will be an issue in some regions. Habitat prediction for benthic species or pelagic species which spend a great deal of time at depth, such as bigeye tuna, *Thunnus obesus* Lowe, or swordfish, *Xiphias gladius* L., would also rely on ocean models to predict the 3D structure of the habitat and perhaps other variables such as prey distribution. The approach outlined is equally applicable to any species for which suitable data exist; such data are being gathered for a variety of top pelagic predators by researchers throughout the world. The dual breakthroughs have been the development of tags that can report vertical water column data on a near real-time basis, and the development of a three-dimensional ocean model that is updated and available to fishery scientists on a space and time scale that is suitable for management uptake. As habitat preferences and distributions are developed for a range of species, tradeoffs between access to desirable species and protected species can also be evaluated.

Forecasts of habitat distribution cannot be made using real-time observations alone, but might rely on statistical descriptions of expected habitat distribution (Lehodey 2001) or ocean forecast models. Forecasts of future habitat distribution at a scale relevant to fisheries managers are likely in the next few years, and will allow a range of management and fishery responses, including forecasts of fishing regions and

decisions regarding quota purchase. This advance will allow even more flexible options for safeguarding sustainability or allow even great exploitation, depending on how information is used (Basson 1999).

Acknowledgments

Satellite data used in the habitat model were provided under a research agreement to CSIRO Marine and Atmospheric Research and the oceanographic model data was sourced from David Griffin and the Bluelink Project. Members of the Pelagic Fisheries 'Spatial Dynamics metaproject' provided input and discussion, in particular Toby Patterson for processing the early PAT data. John Gunn provided much of the early and ongoing support for spatial management options and provided valuable comments, as did two anonymous reviewers who improved the clarity of the manuscript. The AFMA, CSIRO Marine Research, and the Wealth from Oceans Flagship co-funded this work. The Eastern Tuna and Billfish Fishery managers and the AFMA observer programme participants are thanked for their ongoing collaboration.

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