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Seasonal forecasting of tuna habitat in the Great Australian Bight

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ABSTRACT

Commercial fishing involves locating fish in a variable environment, and a fisher's historical experience with environmental conditions and the influence on fish distribution underpins their economic efficiency. However, in many regions, changing environments are reducing the utility of this experience. In the Great Australian Bight, recent environmental changes have modified the summer distribution of southern bluefin tuna (SBT, *Thunnus maccoyii*). This has affected the timing and location of fishing activity and contributed to economic impacts, at the same time as international competition is lowering value of the catch. The SBT purse-seine fishery is managed under a strict quota, so catching more fish is not an option to reduce fixed costs; instead fish must be caught more efficiently in a changing environment. Following discussion with industry stakeholders, we developed a seasonal forecast system based on a three stage process. We first assessed needs through discussions with industry. We then developed a SBT habitat forecast system based on a seasonal environmental forecasting model (POAMA: the Predictive Ocean Atmosphere Model for Australia) coupled with a habitat preference model for SBT (developed using data from tagged fish). Based on a historical evaluation of the environmental forecasting model and the habitat model, we expect temperature-based habitat forecasts to have useful skill up to two months into the future during the months of interest. The final stage involved forecast delivery via an industry-specific website and engagement with stakeholders, which led to improved presentation and contextualization of the forecasts. The forecasts, which are updated daily, are now being used by SBT fishers and have proven a useful aid in their decision-making.

1. Introduction

Fisheries in many countries are an important food source and economic resource. Since fish as a food product competes with other protein sources produced by terrestrial agriculture, minimizing costs of fish production is important for industry profitability (Merino et al., 2012; Pelletier et al., 2014; Plaganyi et al., 2014; Lim-Camacho et al., 2015). In situations where fish harvests are constrained by quota management, reduction of operational costs can be achieved by increasing efficiency in the catching phase. Given that fishing involves locating fish in a variable environment, information on environmental conditions influencing fish distribution can be an important factor in fisher decision-making (e.g., Dell et al., 2011; Hobday and Hartog, 2014), and can reduce costs through minimizing time at sea and identifying optimal times of year to fish. Environmental information can be useful to fishers on a range of time scales from real-time (Hobday and Hartmann, 2006; Howell et al., 2008) to several months into the future (Hobday et al., 2011). Such information is likely to become increasingly important with many fishers encountering novel environmental conditions in space and time (e.g., Nursey-Bray et al., 2012; Pinsky and Fogarty, 2012) and being faced with adapting to a changing climate (Brander, 2010; Bell et al., 2013).

In the southern bluefin tuna (SBT, *Thunnus maccoyii*) purse-seine fishery that operates in the Great Australian Bight (GAB; Fig. 1), fishers use their experience about environmental conditions to plan the start of the fishing season and locate fish. SBT typically arrive in the GAB in December and are resident until March or April each year, before moving back into the Southern Ocean (Bestley et al., 2009; Basson et al., 2012). In this quota-managed fishery, SBT are captured by purse-seine vessels and transferred to tow pontoons for live transport back to Port Lincoln (Fig. 1), where they are fattened for several months before harvest (Bubner et al., 2012). The speed at which tow vessels move (<5 km/h) precludes rapid

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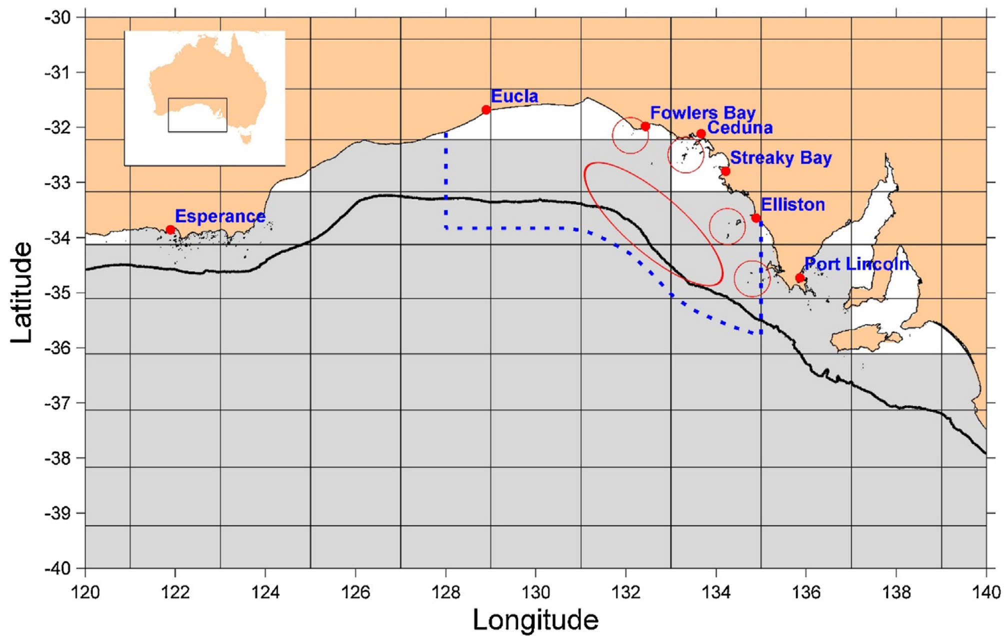

Fig. 1. Map of the Great Australian Bight with the key southern bluefin tuna (SBT) fishing grounds marked by red circles (inshore fishery) and a red ellipse (shelf break fishery). The solid black line marks the 200 m depth contour and approximates the shelf break; the blue dotted line marks the area searched during the annual aerial survey for SBT; and the grid shows the resolution of the seasonal forecasting model (POAMA). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

movements to new areas, so vessels need to be pre-positioned in areas where surface schools of fish are available and abundant. Historical fish distribution patterns are well known, and fishers use this knowledge to determine where to pre-position vessels (Fig. 1). As such, rapid movements of surface schools and the presence of SBT in unexpected locations make fishing operations costly and unpredictable.

In recent years, increased surface temperatures and changes in the spatial distribution of SBT in the GAB have been observed (Eveson et al., 2014b), leading to increased uncertainty in planning fishing operations. In particular, in the 2011–2012 fishing season, for the first time since the start of tuna farming in 1990, SBT were distributed further east than usual (>135°E), resulting in less than 15% of purse-seine catches being taken from fishing grounds reliably used over the previous 20 years (Australian Southern Bluefin Tuna Industry Association [ASBTIA], unpublished data). This unanticipated change resulted in increased costs and a scramble to catch the allocated quota due to limited availability and response times of tow vessels. The following fishing season (2012–2013) also saw unusual SBT distribution patterns that impacted the fishery and fish distribution. As a result of these recent observed changes, the ASBTIA recognized the need for scientific support to improve operational planning in the GAB SBT purse-seine fishery. Some decisions central to planning fishing and farming operations need to be made weeks to months in advance, so industry stakeholders saw a seasonal forecasting system that could provide forecasts of environmental conditions at these lead times as a useful approach.

The Australian Bureau of Meteorology's Predictive Ocean Atmosphere Model for Australia (POAMA) delivers information regarding future environmental conditions on fortnightly to monthly timescales (e.g., Spillman and Alves, 2009; Hudson et al., 2011a). Forecast variables include ocean temperature, sea level, rainfall and air temperature, and can be skilful up to several months into the future, depending on the region and season of interest. Such information is already being used to support decision making for a range of marine industries (Hobday et al., in press). For example, seasonal forecasts of ocean temperature are being used in wild tuna (Hobday et al., 2011), farmed salmon (Spillman and Hobday, 2014) and farmed prawn (Spillman et al., 2015) operations in Australia to reduce uncertainty and manage business risks.

Forecasting environmental variables can be useful to fishers or managers when the focal species responds to environmental conditions in a known way. For example, a simple awareness of temperature distribution in the coming months will be sufficient for some operators to plan their fishing strategy. However, in cases where the environmental responses are not well known to all operators, or the species response is influenced by a range of environmental variables, habitat forecasts for the species in question may be more useful (Hobday et al., 2011). Species-specific habitat forecasts can be made by combining seasonal environmental forecasts with biological habitat preference data. This approach has proven effective as part of the Australian Fisheries Management Authority management of a longline fishery in eastern Australia, where a habitat preference model for SBT based on surface and sub-surface ocean temperatures (conditioned with electronic tag data) has been used to produce maps of predicted SBT distribution off the east coast of Australia (Hobday and Hartmann, 2006; Hobday et al., 2011). Habitat distribution forecast maps provide fishery managers and fishers with valuable insights into expected fish distributions for the upcoming months to better inform operational decisions.

Movement and location data collected on juvenile SBT over many years using archival tags have been used to explore the environmental variables influencing their spatial distribution, and sea surface temperature (SST) was found to be the most influential variable in the GAB (Basson et al., 2012). Here we describe the development of SST-based habitat preference forecasts for SBT in the GAB during the fishing season (December–April). In order to maximize usefulness of these forecasts, they must be delivered in a manner that encourages strong industry awareness and uptake (Marshall et al., 2011; Hobday et al., in press). Thus, we also detail the development of a web-based forecast delivery system in partnership with ASBTIA, and describe the response of industry members to the forecasts and the delivery system.

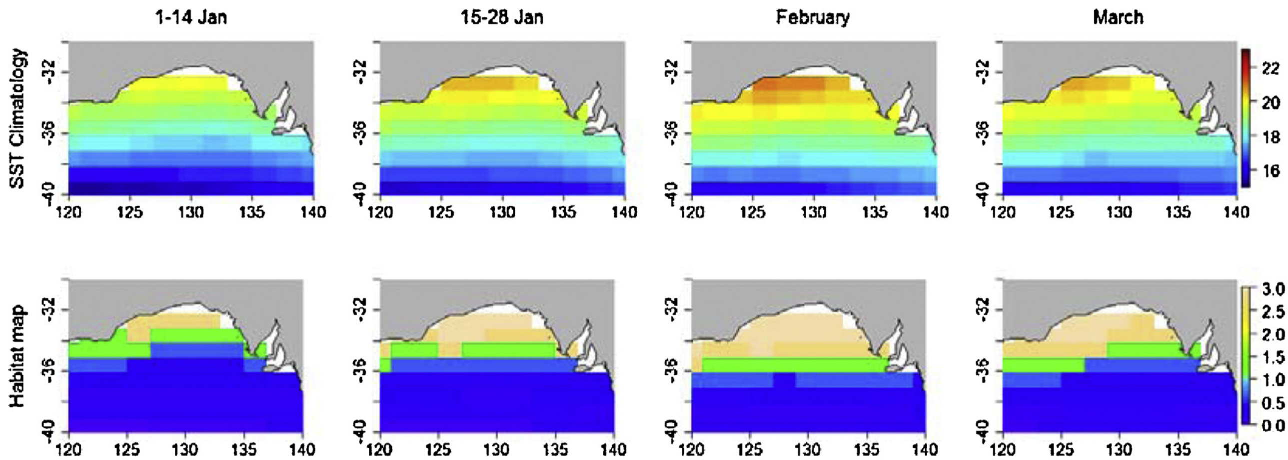

Fig. 2. POAMA climatology, or long-term average sea surface temperature (SST), for 1982–2010 in the Great Australian Bight starting on January 1, for fortnights 1–14 January and 15–28 January, and months February and March (top row), and the derived habitat preference maps (bottom row).

2. Methods

Forecast product development consists of three stages that maximize the chance of successful uptake and use by industries (Hobday et al., in press). The first stage involves assessing the situation in which forecasts will be used, including understanding the critical decisions and time scales for these decisions. The second stage is developing and evaluating skill or accuracy of the forecast products. Forecasts decline in skill with time into the future (lead time), so ensuring that users recognize the limitations of the forecasts is important when developing forecast products. The third and often neglected stage involves evaluation and refinement of the forecast products based on user feedback, in addition to user education and support.

2.1. Stage 1: Assess needs

For this project, the forecast development team, in partnership with an industry liaison representative, scoped the range of operational decisions that were made with regard to obtaining quota, preparing to fish, farming the captured fish, and maintaining fishing vessels and farming equipment. Industry feedback was sought on the types and timeframes of decisions that were likely to be influenced by environmental conditions, and the usefulness of forecasts in supporting these decisions. An important part of the process was to explain to potential users how model forecasts were generated and to develop realistic expectations about the likely performance of forecasts at different lead times. Suggestions for the delivery format of forecasts were also received and used in the next stage (forecast development).

2.2. Stage 2: Seasonal forecast development and evaluation

2.2.1. SST forecasts

POAMA is a global ocean–atmosphere ensemble seasonal forecast system, run operationally at the Australian Bureau of Meteorology since 2002. It comprises a coupled ocean-atmosphere model and data assimilation system for the initialization of the ocean, land and atmosphere (Spillman and Alves, 2009; Hudson et al., 2011a; Hudson et al., 2013). In the real-time system, a 33 member ensemble of daily forecasts is generated by starting the model (POAMA v2) 33 times, initialized only with data available before the start date and running forward in forecast mode for nine months. Initial conditions are provided by two separate data assimilation schemes; an atmosphere/land initialization system (Hudson et al., 2011b) and an ensemble ocean data assimilation system (POAMA Ensemble Ocean Data Assimilation System [PEODAS]; Yin et al., 2011). For each model run (i.e., ensemble member), POAMA provides outlooks based on fortnightly and monthly aggregates of the daily forecasts. The variability of the results among the ensemble members provides information as to the probability distribution of future conditions. However, in this study, we have focused on the ensemble mean forecasts, i.e., the average of the 33 ensemble members. The ocean model grid resolution in the GAB domain is approximately 90–110 km north–south and 200 km east–west (Fig. 1), with upper vertical layers 15 m deep and increasing with water depth. Only forecasts of ocean temperature in the uppermost 15 m layer (i.e., SST) were utilized in this study.

Forecast lead time is defined as the time elapsed between the model start date (date the model forecast is initialized) and the forecast date. In this application we have used ensemble mean SST forecasts for the first fortnight (f1: mean of the first 14 daily forecasts), second fortnight (f2: mean of the second 14 daily forecasts), and the first two calendar months (m1–m2) from the model start date. For the monthly forecasts, the first calendar month (m1) is always the next month after the forecast start date, with the second month (m2) the next after that. For example, for a forecast starting on 11 February, f1 refers to the forecast for the period 11–23 February, f2 to 24 February–9 March, m1 to 1–31 March and m2 to 1–30 April.

A set of mean-adjusted SST forecasts was produced for input to the habitat model. First, SST anomalies were created for each f1, f2, m1 and m2 forecast by subtracting the appropriate fortnightly or monthly POAMA climatology from the ensemble mean forecast SST values. The POAMA climatology is the long-term fortnightly or monthly mean POAMA SST for 1982–2010, computed relative to start date and lead time. As an example, Fig. 2 shows the POAMA climatology for lead times f1, f2, m1 and m2 starting on the 1st of January. The climatology is removed from the forecasted SST values to reduce the effects of any model bias (Stockdale, 1997). Second, the appropriate monthly or fortnightly observed climatology (i.e., the long term fortnightly or monthly mean observed SST for 1982–2010) was added to the POAMA SST anomalies to give absolute temperatures. The SST dataset used for calculating the observed climatology came from the PEODAS ocean reanalysis, which assimilates satellite and in situ data using a pseudo ensemble Kalman filter approach on the ocean model grid (Yin et al., 2011). The term “observed” is somewhat of a misnomer because SST is not directly measured, but rather must be modelled from available data (such as satellite observations) to account for factors such as cloud cover and missing or sparse data. We use the PEODAS reanalysis as our observed SST dataset in

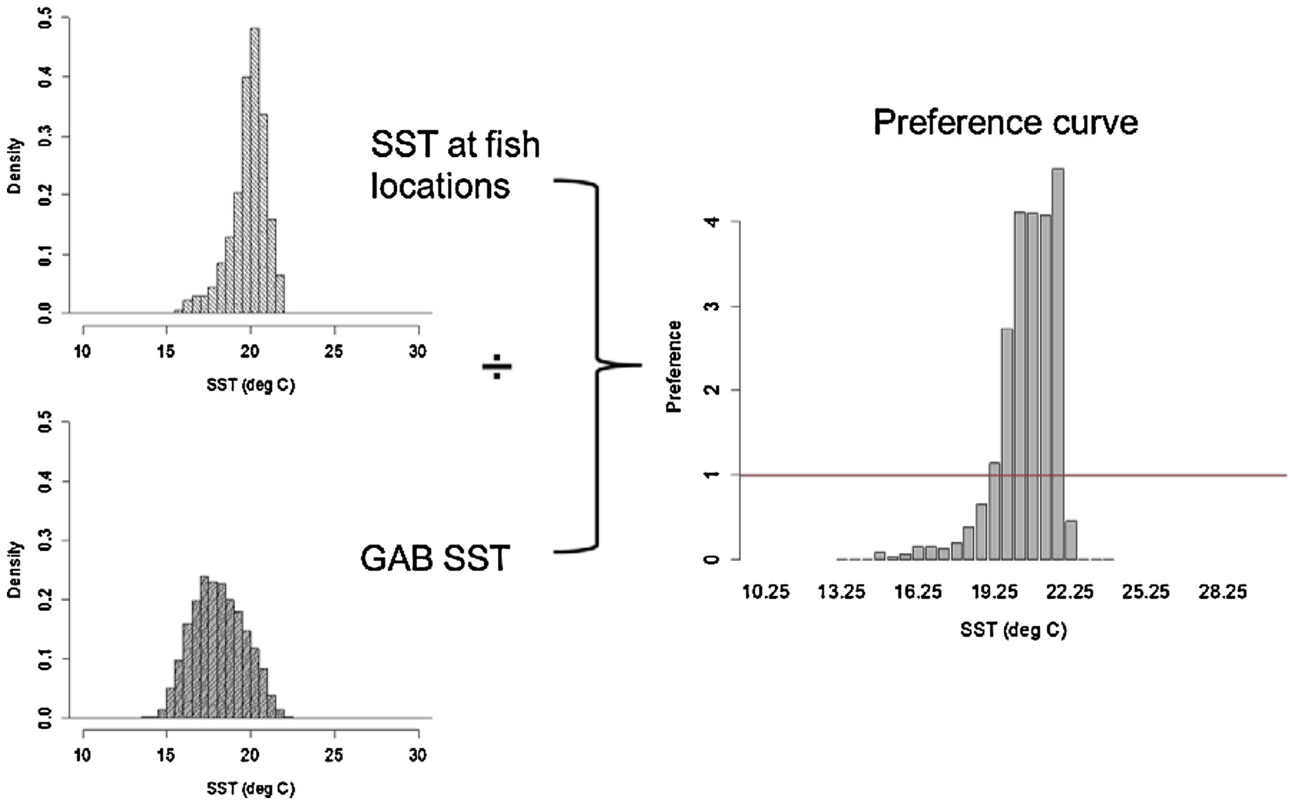

Fig. 3. Habitat preferences of SBT in the GAB based on SST data. The top left shows the distribution (density) of SST values at all locations where fish were found in the GAB during Jan–Mar of 1998–2009 (based on archival tag data). The bottom left shows the distribution of all SST values present in the GAB during Jan–Mar of 1998–2009. The right shows the preference curve derived by dividing the fish distribution by the ocean distribution, where a value>1 indicates the temperature is preferred (i.e., it is found in greater proportion in the fish distribution than in the ocean distribution).

evaluating the POAMA forecasts because it was developed in conjunction with POAMA and has a consistent spatial and temporal range and resolution.

To assess the skill of the POAMA SST forecasts in the GAB, a set of retrospective forecasts (hindcasts) for lead times f1, f2, m1 and m2 was generated by starting the model on the 1st, 11th and 21st of each month (Dec–Mar) for the period 1982–2010, initialized using only data available before the start date. Model skill was calculated by correlating the mean-adjusted POAMA SST ensemble mean values with the observed PEODAS SST values over years 1982–2010 in both space and time using the Pearson correlation coefficient (Spillman and Alves, 2009). For example, for forecasts started on the 1st of January for the first fortnight (lead time f1), the correlation between the 29 years of forecasted and observed SST pairs was calculated within each spatial grid cell. A correlation value of 0.31 or higher is required to be significantly greater than 0 at level 0.05 (one-tailed t-test with test statistic = $\sqrt{(1-r^2)/(n-2)}$ and $(n-2) = 27$ degrees of freedom).

Another metric commonly used to evaluate forecast skill is root-mean-square error (RMSE), which measures both bias and variance of the forecasts. Because the POAMA SST forecasts have been mean-adjusted using the PEODAS observed climatology, there is no bias compared to the observed (i.e., PEODAS) data. The amount that the forecast values vary from the observed is related to correlation, since there must be no variation when the correlation equals 1 (i.e., forecast equals observed in all years), whereas the variation increases as the correlation declines. In fact, if the forecast and observed values are standardized to have zero means and unit variances, correlation and RMSE have a one-to-one relationship (Barnston, 1992). Thus, we have chosen to present only correlation skill here.

2.2.2. Habitat forecasts

Basson et al. (2012) explored environmental variables influencing juvenile SBT spatial distribution using data from archival-tagged fish, and developed winter and summer habitat preference models based on the variables found to have greatest influence–primarily SST, but also chlorophyll *a*. Here we refined the summer habitat preference model using only data from the key months of the fishing season and the region of the GAB where SBT are most commonly found during these months. We also used only SST data since chlorophyll is not a POAMA-forecasted variable. The specific steps were as follows:

(1) We first defined the model region to be the GAB between 30–40°S and 125–140°E and the time period to be the months of January–March in years 1998–2009 (all years for which we have archival tag data).
(2) We then extracted SST data for this region and time period using a 3-day composite satellite SST product produced for the Australasian region (Griffin et al., 2005; available at a temporal resolution of 1 day and a spatial resolution of 0.036° latitude by 0.042° longitude), and averaged it over a 0.1° × 0.1° grid in each Jan, Feb and Mar of 1998–2009.
(3) Next, we used SBT position estimates from historical archival tag data (Hartog et al., 2009) to determine locations where fish were found within the GAB during each Jan, Feb and Mar of 1998–2009, and extracted the subset of SST data (from the dataset compiled in step 2) corresponding to these locations and time periods.
(4) Finally, we compared the SST data from the "fish dataset" (from step 3) with the "ocean dataset" (from step 2) to see which conditions the fish tended to 'prefer'. Specifically, we divided the proportion of fish observations in each 0.5 °C SST bin by

the proportion of ocean observations in that bin. Values greater than 1 indicate the conditions in that bin are "preferred" (i.e., they are found in greater proportion in the fish data than in the ocean data) (see Fig. 3).

We used the 3-day composite satellite SST data as input to the habitat model as opposed to the PEODAS SST data because the satellite data are available on a much finer spatial scale, which is more suitable for modelling habitat preferences.

The ability of the habitat preference model to predict the distribution of SBT in the GAB was evaluated using a dataset of aerial sightings of SBT (Eveson et al., 2014b). An annual aerial survey of the GAB has been conducted in January–March of 1993–2000 and 2005–2014 in which trained observers in aircraft search a defined area (Fig. 1) for schools of SBT. For each month and year with survey data, we initially calculated the proportion of fish spotted within areas of preferred habitat (i.e., α = biomass of fish in preferred habitat/total biomass of fish spotted). However, this value alone is not sufficient to evaluate performance of the habitat model because the entire survey area may have been deemed preferred habitat. Thus, for each month and year, we divided α by the proportion of the total survey area considered to be preferred habitat to get a "score" for that month and year. A score greater than 1 suggests the habitat preference model is informative; i.e., fish are found in greater proportion in areas predicted to be preferred habitat than if they were just randomly distributed (which would give a score equal to 1).

Areas of preferred SBT habitat in the GAB for any given time period (past or future) can be obtained by mapping the preference values corresponding to each SST bin (Fig. 3) to a map of SST values (observed or forecasted). Thus, maps of expected SBT habitat in the GAB derived from real-time POAMA SST forecasts were created for lead times f1, f2, m1 and m2 for different model start dates. The likelihood of the habitat forecasts correctly predicting areas of SBT distribution is linked to SST forecast skill. This means that when considering a habitat forecast for, say, February that was issued on the 1st of January (lead time m1), it is important to consider the skill of the input SST forecast and how it varies spatially. The spatial grid of the POAMA forecasts is relatively coarse (Fig. 1), so the derived habitat forecasts do not provide fine-scale predictions of where SBT are likely to be found, but rather they should be useful for predicting broad-scale distributional patterns (e.g., whether SBT are likely to be present in the eastern GAB in a given month).

The habitat forecasts will be most useful for the SBT fishing industry in times and places where predicted SBT habitat varies amongst years. For example, if habitat forecasts issued on the 1st of January for the month of February (lead time m1) predict the same areas to be preferred SBT habitat every year, they will not be very informative for planning fishing operations. This will depend both on whether SST actually varies enough at a given location to change preference status, and also on whether the SST forecasts are able to predict this variation (for example, the forecasting model may not be able to capture temperature variation close to shore or in areas and times of year with dynamic currents, particularly at longer lead times). To investigate, we derived habitat forecasts from SST forecasts started on the 1st of December, January, February and March at lead times f1, f2, m1 and m2 for all years in the hindcast dataset (1982–2010). For each start date and lead time, we tallied the proportion of years for which each grid cell of the GAB was deemed preferred habitat (i.e., preference value greater than 1). Forecasts for which most grid cells have proportions close to 0 (never preferred) or 1 (always preferred) are likely to be of less interest to industry, as there is relative consistency in the presence or absence of tuna.

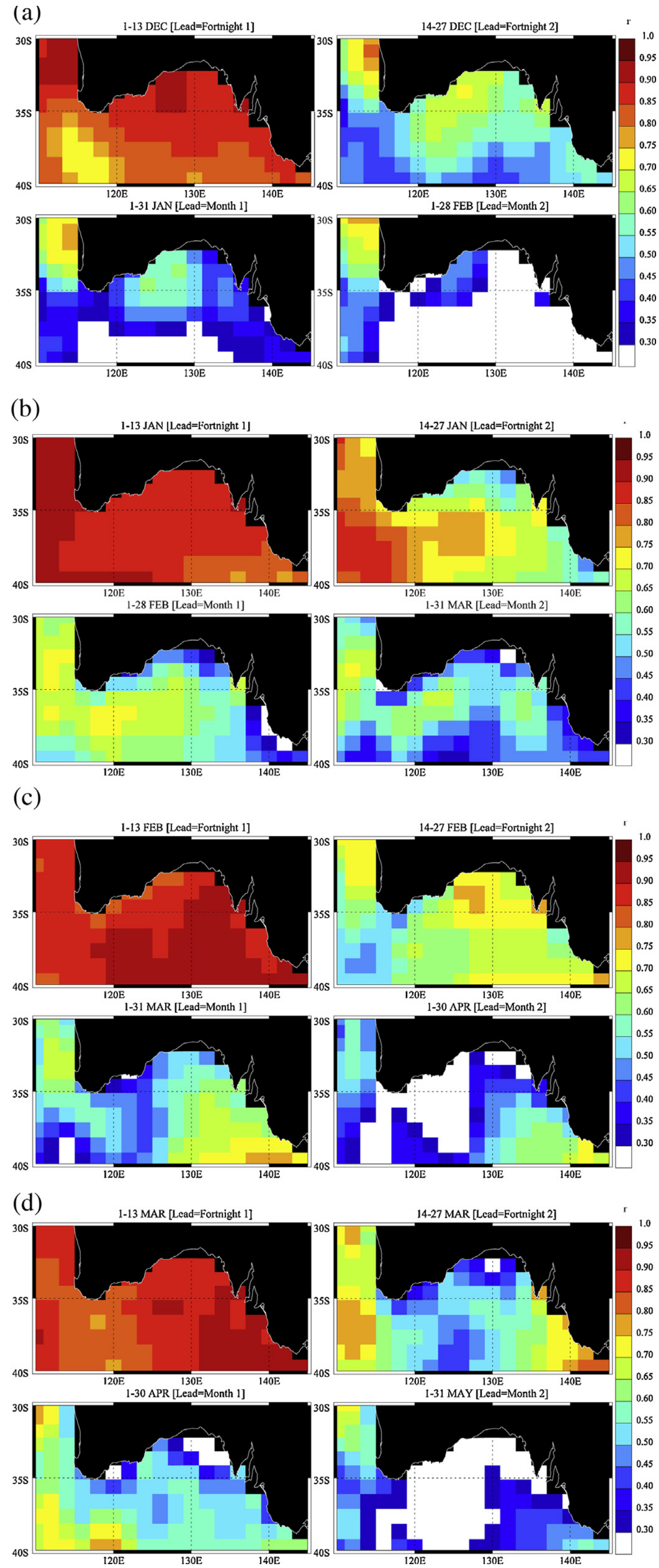

Fig. 4. Skill of sea surface temperature (SST) forecasts started on the 1st of (a) December, (b) January, (c) February and (d) March from 1982 to 2010 for lead times fortnight 1 (f1; top left), fortnight 2 (f2; top right), month 1 (m1; bottom left) and month 2 (m2; bottom right). Skill is measured by Pearson's correlation coefficient (r), where values greater than 0.3 are significantly greater than 0 (one-tailed t-test, significance level 0.05).

2.3. Stage 3: Forecast implementation and feedback

Forecast delivery was implemented using an industry-specific website, with layout and information provided based on discussion with industry representatives during Stage 2 of the forecast product development process. Visits to Port Lincoln (main port for the fishery) by the technical project team complemented the frequent face-to-face discussions on site facilitated by the industry liaison officer. These discussions shaped the material accompanying the forecasts on the website. Formal feedback on how forecasts were used in the first season was also elicited through a short survey delivered in person to industry stakeholders. This survey covered the types of operational decisions that were influenced by the forecasts, in addition to gauging general satisfaction with the forecast explanation, development and delivery.

3. Results

3.1. Stage 1: Assess industry needs

Discussions with the tuna industry prior to developing the forecast products and delivery system showed that forecasts could be useful for a range of decisions that were influenced by environmental conditions. Of the potential decisions in four major categories (quota management, fishing operations, farming operations, and equipment maintenance), a range were potentially influenced by environmental conditions, including fishing start dates, equipment preparation and staff planning, and could be informed by seasonal forecasting of those conditions. Industry reported that different lead times were relevant to these decisions, ranging from real-time to several months ahead. There was variation in awareness of environmental influences and forecasting utility between industry representatives, which emphasized the need for ongoing support and engagement. Concern with changing environmental conditions and fish distribution also led to expressions of support for a forecast system.

3.2. Stage 2: Forecast development and evaluation

3.2.1. SST forecasts

Skill of the POAMA SST forecasts, as measured by Pearson's correlation coefficient (r), for the GAB for model start dates of 1st of December, January, February and March 1982–2010 is shown in Fig. 4. Analogous figures for forecasts started on the 11th and 21st of each month in 1982–2010 are provided in the Supplementary Material (Figs. S1 and S2, respectively). In general, forecast skill is high ($r > 0.8$) for the first fortnight for all start dates and decreases with lead time. However, forecasts started in January (Fig. 4b) tend to maintain greater skill with increasing lead time than the forecasts started in other months. Skill tends to be higher in the west of the domain than in the east. As start dates within each start month increase from the 1st to the 21st, skill improves for the monthly forecasts m1 and m2 across all start months December–March. This is due to decreasing lead time as the time elapsed between the model start date and the forecast date decreases, i.e., for a model start date of 1st January, the February m1 forecast has an effective lead time of 31 days, whereas for a model start date of 21st January, the February m1 forecast has an effective lead time of 10 days. In most instances, skill of the m2 forecasts is poor (i.e., $r < 0.3$, which is not significantly different from 0) over large areas of the GAB for all start months and dates, with the exception of forecasts starting in January.

Table 1
Scores indicating how well the habitat preference model performed at predicting the distribution of SBT aerial sightings in each year and month of the survey. Scores>1 indicate the model is informative (scores<1 are in bold). No SBT were spotted in March 1996.

Year	January	February	March
1994	1.79	1.38	1.18
1995	**0.43**	1.16	1.91
1996	2.35	1.24	–
1997	1.27	1.03	1.18
1998	1.39	1.05	1.11
1999	1.17	1.26	1.55
2000	1.73	1.05	1.06
2005	1.20	1.01	1.41
2006	1.16	1.32	1.08
2007	1.05	1.05	1.08
2008	1.10	1.57	1.02
2009	1.01	1.10	**0.93**
2010	1.02	1.22	1.10
2011	1.00	1.07	2.31
2012	1.01	1.02	1.01
2013	1.06	1.02	1.03
2014	1.02	1.03	1.03

SST forecasts that were issued on the 1st of January in two different years (2005 and 2013) are shown for lead times f1, f2, m1 and m2 in Fig. 5. Compared to the model climatology for the same start date and lead times (Fig. 2), SST in the GAB was forecasted to be similar to average for the 2005 summer (Jan–Mar) and much warmer than average for the 2013 summer. Moreover, when comparing the forecasts with the observed (3-day composite satellite) average SST data for the same time periods (Fig. 5), the forecasts appear to reflect the observed data well at all lead times, with the only exception being the forecast for March made on the 1st of January 2013, which predicted cooler temperatures in the east than were actually observed.

3.2.2. Habitat forecasts

Based on the habitat model, the range of SST values preferred by SBT in the GAB is estimated to be 19–22 °C (i.e., the preference values corresponding to these temperatures are greater than 1; Fig. 3). A comparison of the locations where fish were spotted during the aerial survey with the areas predicted to be preferred habitat showed that the habitat model was informative (i.e., had scores greater than 1) in 48 of 50 month-year combinations of the survey (Table 1).

Forecasts of preferred SBT habitat derived from SST forecasts issued on the 1st of January in 2005 and 2013 are shown in Fig. 5. The habitat forecasts issued on the 1st of January 2013 predicted almost all of the GAB as preferred SBT habitat in January through March. This is due to warm SST anomalies correctly predicted in the 2013 season, so that even in early January, the eastern GAB was forecasted to be warm enough to be preferred SBT habitat. In contrast, SST forecasts issued on the 1st of January 2005 (correctly) predicted much cooler temperatures in the GAB for the 2005 season, particularly in January and in the eastern GAB. Thus, much of the GAB did not fall within the preferred SST range for SBT, and this was reflected in the habitat preference forecasts. It is important to keep in mind that, based on the SST forecast skill evaluation, we would have lower confidence in the habitat preference maps for lead time m2 (March).

Fig. 6 summarizes the annual variability of the habitat forecasts for a given start date and lead time for 1982–2010. During the first half of December, it is rare for any areas of preferred SBT habitat to be forecasted in the GAB. Through late December and early January, the forecasted regions of preferred habitat show increased variability, suggesting that the forecasts may be useful for

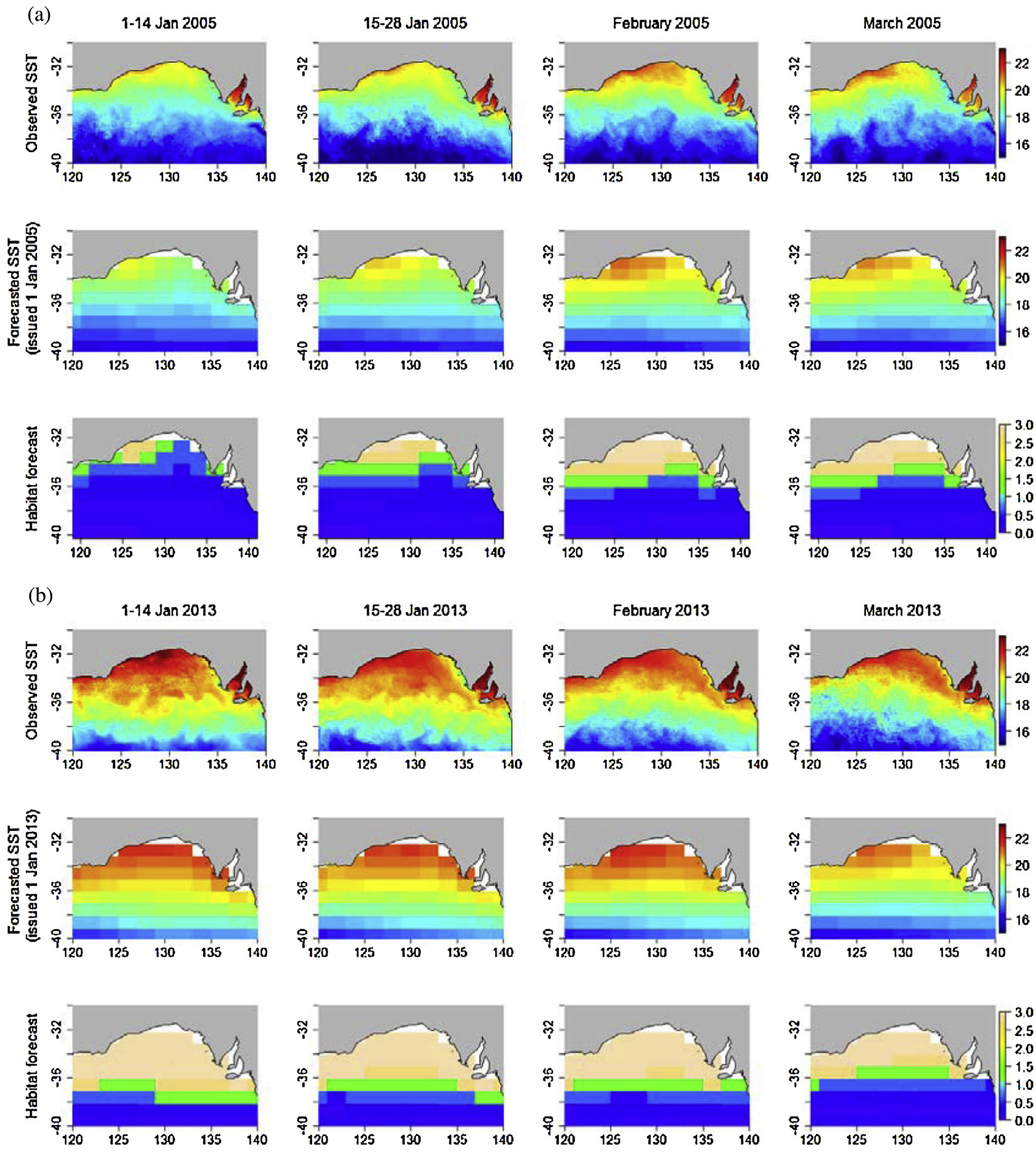

Fig. 5. (a) Sea surface temperature (SST) forecasts (middle row) and corresponding derived habitat preference forecasts (bottom row) issued on the 1st of January 2005 for 1–14 January (f1), 15–28 January (f2), February (m1) and March (m2). Observed average satellite SST for the same periods are shown in the top row. (b) as for (a), but for the year 2013.

predicting whether SBT are likely to migrate into the GAB earlier or later in the fishing season. In February, all grid cells of the GAB above 36°S are almost always forecasted to be preferred habitat. Then in March (particularly in the east) and in April, the forecasted regions of preferred habitat again become more variable, until May when it is rare for any regions of the GAB to be forecasted to contain preferred habitat. This suggests the forecasts may also be useful for predicting when the majority of SBT are likely to leave the GAB in a given season.

3.3. *Stage 3: Forecast implementation and feedback*

A prototype website (www.cmar.csiro.au/gab-forecasts) containing forecasts of SST and preferred SBT habitat in the GAB, and which was designed to update daily, was delivered to industry prior to the first fishing season of the project (2013–2014). The website included interpretation guidance and skill measures to accompany the forecasts, as well as information on current SST conditions. Modifications to the content and format of the website were made

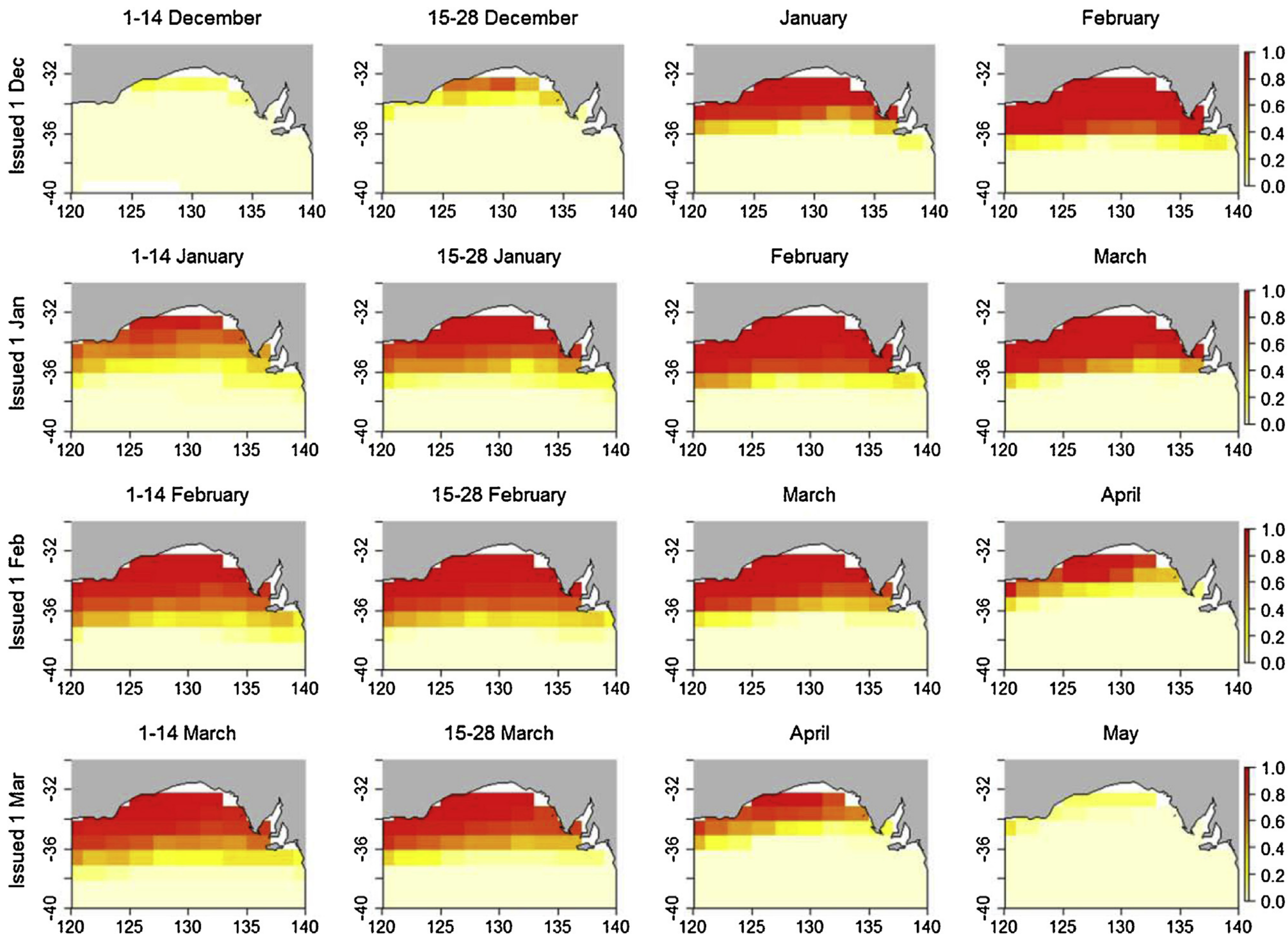

Fig. 6. Proportion of hindcast years (1982–2010) that each grid cell of the Great Australian Bight was forecasted to be preferred SBT habitat, based on forecasts issued on the 1st of a given month (as specified to the left of each row) at lead times f1, f2, m1 and m2 (dates specified at the top of each map). For example, for forecasts issued on 1 December, lead times f1, f2, m1 and m2 correspond to 1–14 Dec, 15–28 Dec, January and February.

frequently in response to informal feedback received throughout this first season. Of note was the interest from industry in having information across time scales from real-time to short-term (<2 weeks) to several months in advance, reflecting their multiple decision making needs.

At the conclusion of the first fishing season (March 2014), industry decision-makers were formally surveyed to determine satisfaction with both forecast format and delivery, and to assess the influence of the forecasts on their decision making. A total of six responses were received from senior decision makers in each of the tuna catching companies (e.g., operations managers, managing directors), plus one response from a senior representative of the associated bait industry. Tuna industry participants had between 14 and 64 years of experience in this fishery. All participants had used the website at frequencies ranging from twice per week up to once for the season. Although the focus of the project was on delivery of seasonal environmental and habitat preference forecasts, information on current and recent (previous week) ocean conditions was considered very useful, with the satisfaction score for information presented ranging from 8/10 to 10/10 (mode 8/10). This historical information was previously available in a range of disparate locations, but industry decision makers considered aggregation in a single location and consistent format highly beneficial. The forecasts were also deemed very useful, with satisfaction scores for information delivery ranging from 8/10 to 9/10. Satisfaction with the overall delivery mechanism (information and forecasts) was rated at between 8/10 and 10/10 (mode 10/10). Of the six participants responsible for decision-making related to capture of SBT in the 2013–2014 season, four reported that they made a decision in response to the seasonal forecasts, such as delaying their fishing start and planning their fishing location. The other two decision-makers regularly checked the forecasts, but decided that no change in their planning was necessary.

Over the course of the project (18 months), stakeholders suggested changes to forecast spatial coverage and requested a range of contextual information to accompany the forecasts. Suggestions included providing maps of recent observational chlorophyll, wind, and salinity fields, a range of historical case studies, and inclusion of tracking data from tagged tuna to illustrate habitat associations. Most of these suggestions were included in revisions of the website delivery system, which generated further opportunities for discussion between project staff and the industry stakeholders, and built end user confidence in the project outputs.

4. Discussion

In partnership with industry representatives from the SBT purse-seine fishery in the GAB, a seasonal forecasting decision support tool that is updated automatically on a daily basis and accessible from a tailored website has been developed. A three stage process was followed to develop the forecast system, and was critical to successful and early adoption of the forecast system (Marshall et al., 2011). While the primary focus was the delivery of fortnightly and monthly forecasts of SST and preferred SBT habitat, in response to feedback from the end users, a range of historical environmental information and case studies were also provided as additional contextual support for decision making. This tool has already been used to assist fishers in making decisions that require forward planning, and places the industry in a better position to respond to environmental change on a range of time scales. Use of this information should enhance the economic efficiency of this fishery, as it will assist fishers in identifying likely SBT distribution weeks to months ahead of time. Because the SBT fishery is quota-managed, the forecasting approach will not lead to increased catches but should enable fishers to catch their quota more efficiently. An essential part of developing the forecasting tool was engagement with industry via face-to-face presentations and regular briefings by the industry co-investigator. Including stakeholders in research projects is increasingly seen as important in knowledge cogeneration (Johnson and van Densen, 2007; O'Keefe and DeCelles, 2013; Cvitanovic et al., 2015). Regular engagement with industry members allowed the project team to explain the forecasts and web delivery system and to receive rapid feedback for making improvements.

Comparison of SST forecasts in the GAB with historical data indicated that the forecasts have sufficient skill (i.e., correlation coefficients significantly greater than zero) up to two months in advance for forecasts started during all months of the fishing season (Dec–Mar), and therefore are useful planning tools. The website provides information on the skill of the SST forecasts, so that decision makers can judge the accuracy of the forecasts and how it declines with lead time. Ongoing conversations with industry and management will lead to greater awareness of the strengths and limitations of forecasts—they can still be inaccurate, but sustained use is likely to lead to more positive outcomes than simply assuming "average conditions" to plan business operations (Marshall et al., 2011; Asseng et al., 2012).

Skill of the habitat forecasts is determined not only by the skill of the SST forecasts, but also on the skill of the habitat model. We were able to show using independent aerial sightings of SBT in the GAB that fish were found in greater proportion in areas deemed preferred habitat by our SST-based habitat model than if they were distributed randomly (i.e., scores, as defined in Section 2.2.2, greater than 1). However, in many months and years of the survey, most of the survey region fell within the preferred SST range so the habitat model was only slightly informative (scores greater than but close to 1). In Eveson et al. (2014a), we showed that when chlorophyll is added to the habitat model the area deemed to be preferred habitat shrinks, whilst still containing the majority of SBT sightings (scores increasing compared to those based on only SST in all months and years except two, with the average score increasing from 1.16 to 1.28).

Seasonal forecasts for this and other marine fishery applications is currently limited with respect to the environmental variables that POAMA can forecast (e.g., ocean temperature); thus, other non-forecasted variables that are important in explaining variation in historical distribution of SBT (e.g., chlorophyll) cannot be included in the habitat forecasts. In future, statistical techniques could be employed to evaluate the co-variation pattern between data that are available (e.g., SST) and unavailable (e.g., chlorophyll) to explore the viability of adjusting future habitat forecasts using that pattern (e.g., principal component analysis, spatial generalized additive models, or other statistical techniques). These improvements are beyond the scope of this establishment phase but may improve the accuracy of forecasts, and increase the lead time at which forecasts can be made.

The spatial resolution of the forecasts provided by POAMA is suitable for a range of offshore fishing and marine management applications (Spillman and Alves, 2009; Hobday et al., 2011), but additional near-shore applications (e.g., oyster aquaculture) are currently limited by this coarse resolution. Extrapolation and downscaling methods that will increase the resolution offshore, and increase coverage for near-shore applications, are in development (e.g., Oliver and Holbrook, 2014).

In deriving our habitat forecasts, we only made use of the POAMA ensemble mean SST forecasts. To assess variability in the habitat forecasts due to variability in the SST forecasts, we could derive a habitat forecast for each of the 33 ensemble SST forecasts and report the mean and variance preference value in each grid cell. Alternatively, a more probabilistic forecast could be given by calculating the proportion of times a grid cell is preferred (i.e., the proportion of times that a grid cell has a preference value greater than 1 across the 33 ensemble forecasts). As end-users become more sophisticated in their interpretation and usage of the habitat forecasts, such information may be in demand (see Spillman and Hobday, 2014).

The habitat preferences of SBT were determined based on the environmental conditions present at the locations where fish were found, where fish locations were estimated from archival tag data. The uncertainty in position estimates derived from archival tags can be large, particularly in the latitudinal direction (e.g., Musyl et al., 2001; Nielsen et al., 2009), and this forms an important source of uncertainty in the habitat model. If the position estimates are biased in a particular direction, this could bias the habitat preference range; otherwise, if the error is random, it could lead to an increased preference range, whereby some undesirable areas may be identified as desirable. A goal for future is to improve the habitat model by including uncertainty in the position estimates (e.g., by bootstrapping the positions and re-estimating preferences). Another limitation with the habitat model is that data are only available for certain environmental variables, and for limited years and regions, thus we may be missing a key variable influencing the fish distribution. Furthermore, for any environmental variable found to be associated with fish location (e.g., SST), we do not know whether this variable has a direct influence, or if it is a proxy for something else (e.g., prey distribution). If the relationship between the environmental variable and its proxy changes, the habitat forecasts would no longer be valid. Thus, it is important to update the habitat model periodically with new data to check for changes—whether they be due to animals altering their preferences with regard to a given variable, or to the relationship between the variable and its proxy changing.

An important challenge is to ensure long-term delivery of forecasting information, once developmental research projects have concluded (Marshall et al., 2011). Here we developed procedures such that forecasts available from the website can be updated automatically for use in subsequent seasons. However, a number of issues can complicate ongoing forecast delivery. First, problems such as loss of satellite data coverage or loss of internet services could disrupt forecast delivery and potentially lead to cessation of forecast capability. Second, the seasonal forecasting model being used (POAMA) is likely to be updated in future; this may require changes to the computer code that generates the forecasts as well as evaluation of the skill of the new forecast model. Third, the habitat forecasts are based on habitat preferences derived from biological data collected on SBT during 1998–2009 from archival tags. SBT habitat preferences may change in future, particularly given the increasing trend in temperature in the GAB over recent years (see www.cmar.csiro.au/GAB-forecasts/historical-sst.html). Thus, as already noted above, the habitat model should be updated periodically using new biological data (e.g., from archival tags) to ensure the habitat forecasts remain relevant. The collaborative approach taken in developing this system should also assist with ongoing use of the forecast system, as one of the co-investigators is based in the main SBT fishing port (Port Lincoln) and regularly provides updates and briefings on the forecasts. Time will tell if this approach will overcome some of the traditional challenges with user uptake of seasonal forecasting, but it parallels the use of extension officers in agricultural forecasting projects (Marshall et al., 2011).

Despite early use and satisfaction of SBT industry stakeholders with the forecasting system, measuring improvements in economic efficiency as a result of using these forecasts will be difficult. Fishing decisions and strategies are related to a range of factors beyond just environmental considerations, such that relating even simple metrics such as reduced fuel costs with forecast use are likely to be fraught. Development of new technologies, changes in policy, and market conditions will also play an important role in the particular fishing strategy employed. Despite difficulties in demonstrating economic impact, industry feedback indicates that seasonal forecasts are a useful tool in supporting effective marine management. These forecasts may also represent a useful stepping stone to improved decision making and industry resilience at longer timescales (Hobday et al., in press), such as helping fishers prepare for effects of climate change. Overall, the three-stage model for developing a forecasting system for this fishery was successful in all stages. The forecast system was developed in response to industry needs, it was evaluated and shown to be useful, and it is currently being used by fishers with prospects for enduring use and for enhanced profitability in a time of change.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2015.05.008

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