

# Seasonal forecasting of tuna habitat for dynamic spatial management

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**Abstract:** Capture of the target, bycatch, and protected species in fisheries is often regulated through spatial measures that partition fishing effort, including areal closures. In eastern Australian waters, southern bluefin tuna (SBT, *Thunnus maccoyii*) are a quota-limited species in a multispecies longline fishery; minimizing capture by nonquota holders is an important management concern. A habitat preference model (conditioned with electronic tag data) coupled with ocean reanalysis data has been used since 2003 to generate real-time predicted maps of SBT distribution (nowcasts). These maps are used by fishery managers to restrict fisher access to areas with high predicted SBT distribution. Here we use the coupled ocean–atmosphere model, POAMA (predictive ocean atmosphere model for Australia), and a habitat model to forecast SBT distribution at lead times of up to 4 months. These forecasts are comparable with nowcasts derived from the operational system, and show skill in predicting SBT habitat boundaries out to lead-times of 3–4 months. For this fishery, seasonal forecasts can provide managers and fishers with valuable insights into future habitat distributions for the upcoming months, to better inform operational decisions.

**Résumé :** Les captures des espèces ciblées, accessoires et protégées dans les pêches commerciales sont souvent règlementées au moyen de mesures spatiales qui partitionnent l'effort de pêche et qui incluent aussi des fermetures de zones. Dans les eaux de l'est de l'Australie, le thon rouge du sud (SBT, *Thunnus maccoyii*) est une espèce règlementée par des quotas dans une pêche multispécifique à la palangre; la minimisation des captures par ceux qui ne possèdent pas de quota est une importante préoccupation de gestion. Un modèle de préférence d'habitat (conditionné avec des données provenant d'étiquettes électroniques) couplé à des données de réanalyse de l'océan sert depuis 2003 à produire des cartes de la répartition prédite des SBT en temps réel (prévisions immédiates). Ces cartes servent aux gestionnaires de la pêche pour restreindre l'accès des pêcheurs aux zones dans lesquelles on prédit une forte répartition des SBT. Nous utilisons ici le modèle couplé océan–atmosphère POAMA (Predictive Ocean Atmosphere Model for Australia) et le modèle d'habitat afin de déterminer la répartition des SBT pour des périodes futures allant jusqu'à quatre mois. Ces prédictions sont comparables aux prévisions immédiates dérivées du système opérationnel et se montrent capables de prédire les frontières de l'habitat jusqu'à des périodes futures de trois à quatre mois. Dans cette pêche commerciale, les prédictions saisonnières peuvent fournir aux gestionnaires et aux pêcheurs des perspectives précieuses sur les répartitions futures des habitats pour les prochains mois afin d'établir des bases sérieuses pour les décisions opérationnelles.

[Traduit par la Rédaction]

## Introduction

In many fisheries, the capture of the desired target species is accompanied by the capture of other species (bycatch), including protected species (Hall 1998; Tuck et al. 2001; Lewison et al. 2004). Improvements in gear selectivity have reduced the amount of bycatch in some cases, such as prawn and trawl fisheries (e.g., Griffiths et al. 2006; Ward et al. 2008). In fisheries where gear modification cannot be used to select particular species, spatial identification of core habitat has been proposed to manage unwanted interactions (e.g.,

Goodyear 1999; Grantham et al. 2008). Core habitat can be identified via physiological studies, species observations, catch data, and from electronic tags. Information on the environmental preferences of a wide range of pelagic target and bycatch species has been collected using electronic tags (Block et al. 2003; Weng et al. 2005; Wilson et al. 2005). A goal in many of these tagging studies has been to generate habitat preference maps that can be used in fishery management (Hobday and Hartmann 2006; Teo et al. 2007; Hobday et al. 2009).

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Real time spatial management has been used in the multi-target species Australian east coast longline fishery (Eastern Tuna and Billfish Fishery, ETBF) to minimize unwanted capture of southern bluefin tuna (SBT, *Thunnus maccoyii*) since 2003 (Hobday and Hartmann 2006; Hobday et al. 2009). SBT habitat preferences based on historical pop-up satellite archival tag (PSAT) data are combined with near real-time satellite sea surface temperatures and altimeter-based estimates of subsurface ocean temperature (SynTS; Ridgway and Dunn 2010) to describe three zones of expected SBT distribution (Hobday and Hartmann 2006). These zones correspond to regions where few SBT are found and fishing is unrestricted (OK habitat), the region where most SBT are expected (core habitat) and an intermediate region (buffer habitat) (Hobday et al. 2009; Hartog et al. 2011). The name “OK zone” has been used by the fishery since 2003, and refers to the zone being “OK for fishing without restrictions”. The resulting habitat map is essentially a nowcast, i.e., a depiction of current conditions, as opposed to a forecast, which is a prediction of future conditions.

Based on this habitat nowcast, three corresponding management zones are then created by fishery managers in the ETBF. Access by ETBF fishers to these zones is regulated based on the level of observer coverage and on the amounts of SBT quota they are holding (Hobday et al. 2009), and enforced with observer coverage and vessel monitoring systems. The habitat nowcast and management update of the zones occurs approximately every 2 weeks during the period when SBT are commonly captured in the ETBF (May–November). Over time, the management lines that divide the zones have become more complex and are updated with greater frequency during the fishing season, resulting in reduced interaction with SBT (Hobday et al. 2010). Several similar spatial management approaches have been proposed elsewhere in the world to minimize the bycatch of billfish (Goodyear 1999), tuna (e.g., Teo et al. 2007; Armsworth et al. 2010), and turtles (e.g., Howell et al. 2008). For example, the scheme described by Howell et al. (2008) is based on a voluntary regulation of fishing activity based on the real-time distribution of isotherms that delineate core turtle habitat (Pacific Islands Fisheries Science Center).

Both voluntary and compulsory spatial management strategies result in limits on where fishing operations can occur. Information about the likely future habitat distribution may offset some of the disadvantages arising from spatial restrictions (e.g., Armsworth et al. 2010) and allow fishers and managers to plan activities and regulation. For example, in the case of operational SBT habitat nowcasts in the ETBF, the climatology is provided with each habitat nowcast. A climatology is a long-term average, and in this case, is composed of the average position of the habitat boundaries of predicted SBT habitat for each day of the year over a 16 year period (1993–2008). The SBT habitat boundaries for the current year are plotted against this climatology to allow managers and fishers to plan ahead based on how present SBT habitat conditions vary from the long-term mean (Fig. 1).

The seasonal cycle of SBT habitat is strongly influenced by that of the East Australia Current (EAC; Ridgway and Godfrey 1997). The EAC is a southward flowing western boundary current between 18°S and Tasmania, and is a re-

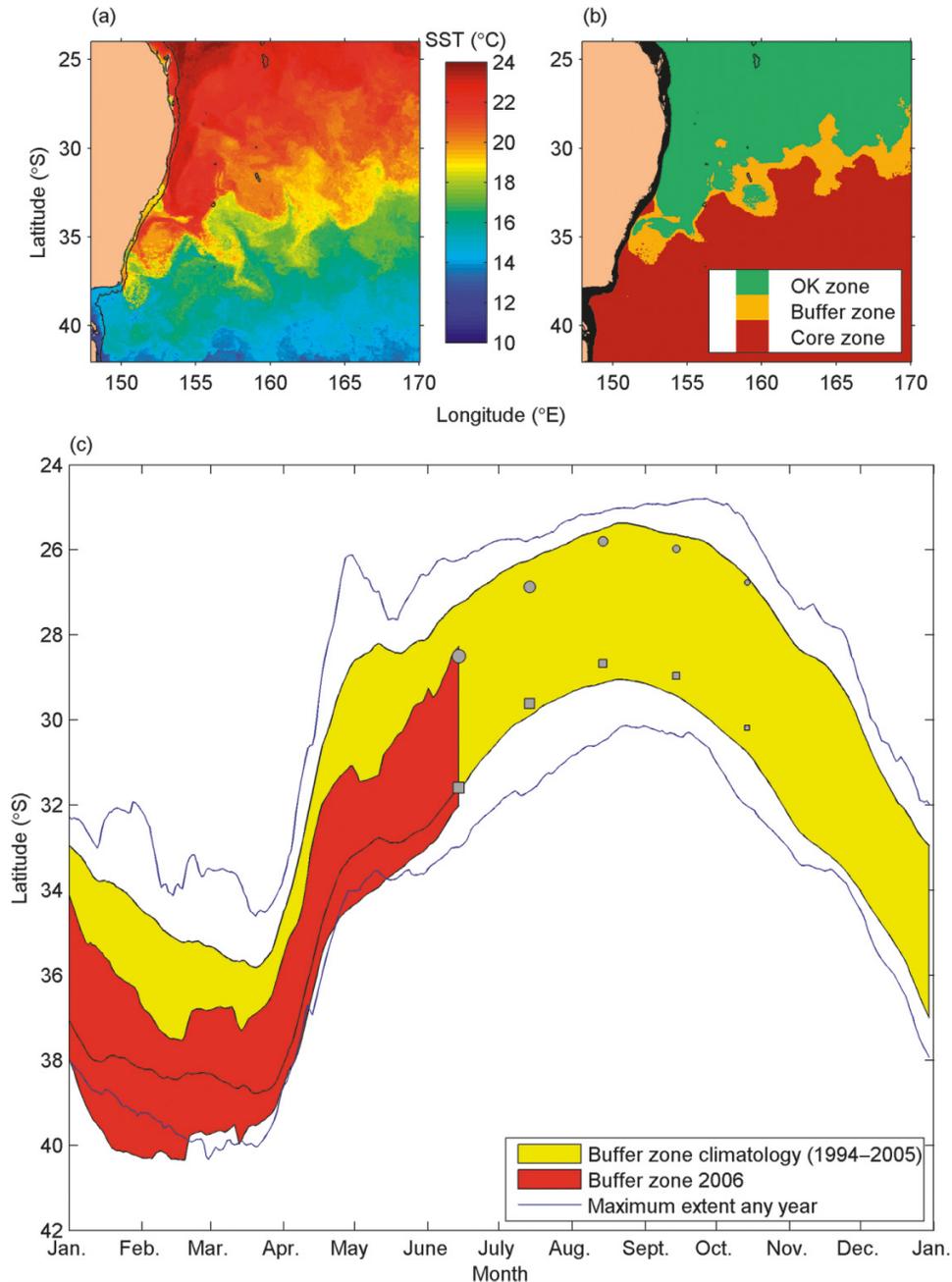
gion of intense eddy activity. The current is generally stronger and closer to the coast in summer (December–March) than in winter (Tomczak and Godfrey 1994). In warmer-than-average years, when the EAC moves further south, SBT habitat is also compressed to the south, while in cooler years, SBT habitat, and hence spatial management restrictions, are found further north than usual. In the east coast region considered, the core zone is typically 60% of the study area (24°S–42°S, 148°E–170°E), the buffer zone is approximately 30%, and the remaining fraction of the study area (10%) is the OK zone (Hobday et al. 2010).

More robust predictions can potentially be made using seasonal forecast models, as climatological approaches may have limited value in regions with substantial interannual variability and under a changing climate. Seasonal predictions can be used to provide managers and fishers with more information about likely ocean conditions several months into the future. These predictions may be based on statistical relationships derived from historical data (e.g., Penland and Matrosova 1998; Lima et al. 2009), or multivariate dynamic model simulations (e.g., Kirtman et al. 1997; Spillman et al. 2010b). For example, the Australian Bureau of Meteorology dynamic seasonal forecast model POAMA (predictive ocean atmosphere model for Australia) is used to issue operational El Niño Southern Oscillation (ENSO) and equatorial Indian Ocean sea surface temperature (SST) forecasts, both of which have high skill (Wang et al. 2008; Lim et al. 2009; Zhao and Hendon 2009). POAMA is also used to forecast SST anomalies in the Great Barrier Reef up to 6 months into the future (Spillman and Alves 2009; Spillman et al. 2009, 2010a). Advance warning of anomalously warm ocean temperatures, the primary cause of mass coral bleaching (Hoegh-Guldberg 1999), allows for proactive management responses to minimize reef damage. The forecasts form an integral part of the Great Barrier Reef Marine Park Authority Coral Bleaching Response Plan and reef management plans (Maynard et al. 2009). POAMA is also used to issue operational ENSO forecasts.

Seasonal prediction also has the potential to be very useful in fishery management. Fishery managers may use seasonal forecasts to manage expectations about upcoming management restrictions, guide observer deployments, or plan other management interventions. A longer-term view can also be useful to fishers, who may need to plan vessel movements or port usage (rental of moorings, crew movements), and to purchase or sell access rights or quota based on expected ocean conditions that may influence management decisions. Fishing strategies may also change, based on the expectation of when a fishing region will receive additional effort from fishers who are displaced from closed areas, or who move into open areas (Armsworth et al. 2010). As an initial step, it is necessary to assess whether seasonal forecast models can offer improved habitat predictions compared with those derived from climatologies. To date, we know of no fisheries that use seasonal forecasting ocean models in management. However, rapid advances in model development and information on fish habitat preferences are increasing the potential use of seasonal models in fisheries management, and it is being considered in the ETBF.

Here we use the POAMA seasonal forecast model coupled to the existing SBT habitat preference model to generate

**Fig. 1.** (a) Sea surface temperature maps, and (b) southern bluefin tuna (SBT) habitat nowcast maps using the operational SBT habitat model for 15 June 2006. (c) Daily operational nowcast climatology of SBT habitat zones, with example operational nowcast boundaries shown for 15 June 2006. The monthly mean position of the boundaries between core and buffer zones (lower line), and buffer and OK zones (upper line) for 1994–2005 is indicated by the yellow band. The blue lines indicate the maximum northerly and southerly extent of these boundaries recorded during the period. The position of the habitat boundaries in the current year (2006) up to the date of the current habitat nowcast (15 June) is depicted by the red band. SBT habitat nowcast maps and climatology are updated online approximately every 2 weeks during the fishing season (AFMA 2011). Grey squares and circles represent forecasts from the predictive ocean atmosphere model for Australia (POAMA) for the location of the habitat boundary for future months, with decreasing size indicating a reduction in skill levels the farther into the future the predictions are made.



monthly habitat forecasts for SBT. Firstly, we compare monthly habitat nowcasts produced using the BLUElink Reanalysis (BRAN; Schiller et al. 2008) with nowcasts from the existing operational habitat system. BRAN is considered to be an improved representation of the ocean compared with SynTS (Oke et al. 2008), so replacing SynTS is desirable.

We then assess the performance of POAMA habitat forecasts, using the BRAN nowcasts as the new benchmark. In particular, we evaluate the skill of POAMA predictions of future SBT habitat at lead-times of 0–4 months to determine whether POAMA predictions of the location of future SBT habitat improve upon climatological estimates. If skill is

present, seasonal forecasting could offer fishers and managers additional insight into future ocean, fishing and management conditions.

## Materials and methods

### Ocean temperature reanalysis and forecast products

Three ocean temperature products were used in this study to drive a statistically based SBT habitat model. Two are derived from ocean data reanalysis products, and the third is a coupled dynamic ocean–atmosphere model capable of seasonal forecasting (Fig. 2). An ocean reanalysis is an assimilation of past ocean data, often using very sophisticated techniques, to give a three-dimensional (3D) depiction of the ocean state at a particular time in the data period. A reanalysis is generally used as observations, or the best estimate of the ocean state, against which to validate model forecasts. Use of this data to drive a secondary model gives rise to essentially what is termed a nowcast, i.e., a representation of current conditions. Coupled ocean–atmosphere models are based on physics and predict future ocean conditions, based only on the best available knowledge of the present ocean state. A hindcast is a retrospective prediction of past conditions, initialised only with information available before the hindcast start date, and run forward in time in forecast mode. A forecast is generated in a similar way but is done in real-time to predict future conditions.

When comparing the variability of different products, anomalies are commonly used, i.e., the deviations about the mean. In this study these are created by removing the monthly climatology from the monthly values, where the climatology is the long-term average for each month over a substantial period of time. A climatological forecast uses these long term mean values as forecasts for each future month and assumes there is no interannual variability.

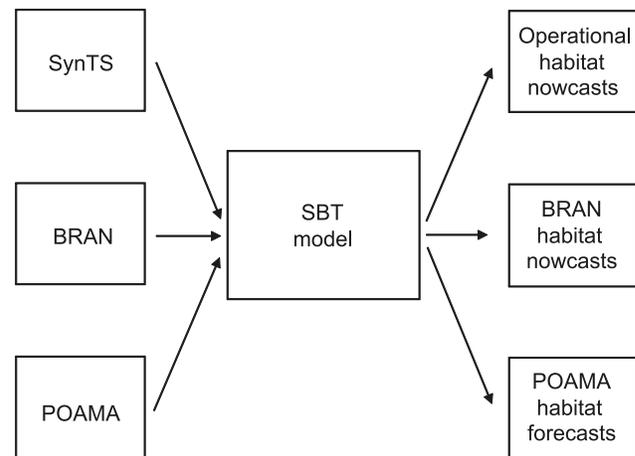
Conversely, a persistence forecast uses the current observed conditions as a predictor of future conditions: e.g., for a forecast beginning on 1 May 2003, the current observed conditions for April 2003 are used as the forecast and persisted for the duration of the forecast period. Persistence is a commonly used benchmark in seasonal forecasting (e.g., Barnston et al. 1999; Wang et al. 2002; Doblas-Reyes et al. 2005), and is often used as a minimum skill forecast, with model skill beyond that of persistence attributed to model dynamics. The correlation skill of persistence forecasts is equal to the skill assuming a first order autoregressive process (AR1).

### Operational reanalysis (SynTS)

The reanalysis product SynTS is used to generate the operational habitat nowcasts. A mean ocean state field for 1992–present is derived from CTD surveys and Argo floats or Australian waters (100°E–180°W; 50°S–10°N), using sophisticated spatial interpolation schemes (Ridgway and Dunn 2010). Satellite altimetry sea level anomalies are used to directly correct sampling errors in surface heights, salinities, and temperatures, with corrections projected through the water column using an empirical model to modify the mean subsurface fields. The empirical model is based on a multiple linear regression technique (SynTS) using on independent ocean data for 1950–1992 (Ridgway and Dunn 2010). The

**Fig. 2.** Habitat maps for the distribution of southern bluefin tuna (SBT) are produced using three sources of ocean information: SynTS, BLUElink Ocean Reanalysis (BRAN), and the predictive ocean atmosphere model for Australia (POAMA). Nowcasts using SynTS and BRAN were first compared to determine whether BRAN was suitable for comparison with POAMA as explained in the text.

Ocean Information → SBT habitat model → SBT habitat maps



reanalysis has a daily temporal resolution and horizontal resolution of  $\sim 28$  km ( $0.25^\circ$ ), with 25 depth layers in the upper 200 m.

### Ocean reanalysis (BRAN)

The BLUElink Ocean Reanalysis (BRAN) is a global ocean reanalysis, produced using a global high-resolution Ocean General Circulation Model (OGCM) and an advanced data assimilation scheme (Oke et al. 2008; Schiller et al. 2008). Altimetric sea-level anomalies, satellite SST, and in situ temperature and salinity profiles for 1993–2006 were assimilated, giving a cohesive picture of the monthly mean observed state of the ocean for this period (Schiller et al. 2008). The spatial resolution of BRAN is  $0.1^\circ$  ( $\sim 10$  km) in the horizontal and 10 m in the vertical down to 200 m. Temporal resolution is daily, although we have used monthly averages here for comparison with the monthly seasonal forecasts.

### Seasonal forecast model (POAMA)

POAMA (version 1.5b) consists of a global coupled ocean–atmosphere model and data assimilation systems for the initialisation of the ocean, land, and atmosphere, and was developed jointly by the Australian Bureau of Meteorology and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) Division of Marine and Atmospheric Research. The atmospheric model component has a horizontal spectral resolution of T47 (roughly equivalent to  $2.5^\circ \times 2.5^\circ$ ) and 17 vertical levels. The ocean model grid spacing is  $2^\circ$  in the zonal direction and  $0.5^\circ$ – $1.5^\circ$  in the meridional direction, with 25 vertical levels, of which 12 are in the upper 185 m. Further details can be found in Spillman and Alves (2009) and Spillman et al. (2010b).

A 10 member ensemble of retrospective forecasts (hindcasts) was generated by starting the model 10 times on the first day of each month for 1993–2006, initialized only with ocean information available before the start date and running forward in forecast mode for 9 months. Lead-time is defined

as the time elapsed between the model start date and the forecast date, i.e., if the start date is 1 May 2003 and the forecast is for August 2003, the forecast lead-time is 3 months, while the forecast for May 2003 is defined as lead-time 0 months. Generally forecast accuracy is highest for lead-time 0 months and decays as forecasts predict further into the future (i.e., increasing lead-time). Ensemble members are averaged to give the overall ensemble mean forecast, which is used throughout in this study.

To assess the accuracy of the POAMA temperature forecasts, the heat content of the upper ocean was used to give a depth integrated indication of skill. Skill is calculated by correlating POAMA heat content forecasts with observed heat content from BRAN in both space and time for 1993–2006. The correlation coefficient ( $r$ ) is defined as the ratio of the covariance of POAMA and BRAN heat content to the product of their standard deviations, with a skill value of 1.0 indicating a perfect fit between model and observed values. Comparisons at a range of depths with BRAN show that POAMA has highest skill in the top 100 m, with temperatures underestimated below this depth.

### Southern bluefin tuna habitat predictions

The SBT habitat model is based on thermal habitat preferences of adult SBT, derived from PSAT deployed on the east coast of Australia (Patterson et al. 2008). Temperature preferences from the historical tag-based dataset are stratified according to depth, and used as weightings within the model for the average time SBT spend at each depth. The model is then forced with either observed or predicted ocean temperatures to determine the location of preferred SBT habitat at a particular time. The resulting habitat preference is the vertically integrated probability of SBT occurrence in each pixel or grid cell (i.e., at resolution of the forcing ocean temperatures) in the eastern Australia region (see Hobday and Hartmann 2006; Fig. 1b). Depths were restricted to the upper 100 m, owing to lower skill below this depth in the POAMA forecasts. According to the archival tags, SBT spend 90% of their time shallower than 200 m, and 74% shallower than 100 m; thus we considered the upper 100 m to be satisfactory in this study. Habitat preferences were produced for each month of the fishing season (May–November) for 1994–2006 using the SynTS reanalysis, BRAN reanalysis, and POAMA forecast ocean temperatures (Fig. 2).

The probability of an SBT being found at a location (pixel) is based on cumulative probability of temperature preferences in the model domain (24°S–42°S, 148°E–170°E). For example, the 80% value in the probability distribution indicates the temperature below which 80% of SBT are expected to occur. This continuous habitat preference is simplified to create three distinct habitat zones: the core zone is defined as the area in which SBT spend at least 80% of their time based on habitat preferences; the buffer zone, where SBT spend only 15% of their time (i.e., the 80%–95% probability region), and the OK zone, where SBT are expected less than 5% of the time (i.e., the 95%–100% probability region). The latitudes at which 95% of the core pixels and 95% of the buffer pixels occur (both counting from the south) are referred to hereinafter as the core and buffer habitat boundaries, respectively (as in Hobday and Hartmann 2006).

### Operational habitat nowcasts

Operational habitat nowcasts are produced every 2 weeks for ETBF managers during part of the fishing season. The habitat model inputs for these nowcasts are temperature data from the SynTS ocean reanalysis for the upper 100 m. In operational usage, satellite SST data is used for the surface layer in the habitat model (previously called “BLUElink-based products” in Hobday and Hartmann (2006)) but was replaced by the surface layer of SynTS in this study, to account for the missing data owing to cloud cover in the satellite SST product. SynTS was produced in real time in the past, thus was suitable for use in operational forecasting; however, an improved product, BRAN, is now available, and is evaluated here to replace the SynTS product.

### BLUElink ocean reanalysis habitat nowcasts

BRAN habitat nowcasts were generated for each month of 1994–2006 using ocean temperatures in the upper 100 m of the BRAN reanalysis to force the SBT habitat model. BRAN habitat nowcasts are first compared with the SynTS operational nowcasts to ensure that using the two different observational reanalysis products does not result in significantly different results, and thus BRAN nowcasts are suitable for comparison with the seasonal model forecasts. These BRAN nowcasts are then used for verification of forecasts produced by POAMA, as BRAN is considered to be a more accurate representation of ocean state than the SynTS product used operationally. We used a monthly average of BRAN for compatibility with the seasonal model.

### Predictive ocean atmosphere model for Australia seasonal habitat forecasts

The habitat model inputs for the seasonal habitat predictions were scaled monthly POAMA ocean temperature forecasts for the upper 100 m. To scale the POAMA monthly ocean temperatures, first the model monthly climatology was removed to create temperature anomalies. The model climatology is the long-term monthly mean ocean temperatures for 1993–2006, computed relative to start month and lead-time for the model, and is removed to reduce the effects of any model bias (Stockdale 1997). The temperature anomalies were then interpolated and smoothed to match the BRAN spatial grid, i.e., ~10 km in the horizontal and 10 m in the vertical direction. Second, the BRAN monthly climatology for 1993–2006 was then added to the anomalies to give absolute temperatures. This approach scales the mean of the forecast but not the variability, the latter being the primary aim of predictions, i.e., how much each month deviates from the long term mean. POAMA habitat forecasts were then generated using the scaled POAMA ocean temperatures for each month at lead-times of 0–4 months for the period 1994–2006.

### Persistence habitat forecasts

BRAN habitat nowcasts were also used to create persistence forecasts for comparison with POAMA forecasts. A persistence forecast simply uses current observed habitat locations as a predictor of future conditions, e.g., if the habitat latitude boundary nowcast is currently 1° further north than the climatology, that differential is maintained for future dates in the coming season.

### Metrics for habitat comparisons

Latitude anomalies were used to compare the core and buffer boundary locations between the operational nowcasts, BRAN nowcasts, and POAMA forecasts. These were calculated by removing the monthly latitude boundary climatology from the boundary values (e.g., May 2003 minus May average across all years). For BRAN nowcasts, latitude anomalies are derived using the average BRAN habitat boundary location for each month of 1994–2006. Similarly, for POAMA habitat forecasts, latitude anomalies are derived using the mean POAMA boundary location for each month at each lead-time in the same period.

We first compared habitat boundary locations of the BRAN nowcasts with those of the operational nowcasts. This was done to ensure the BRAN nowcasts were suitable as a substitute for the operational nowcasts for comparisons with POAMA forecasts. Preliminary analysis showed the monthly BRAN nowcasts and operational nowcasts agreed well, with average monthly differences in boundary location of less than 0.25° latitude for 1994–2006.

We then validated POAMA habitat forecasts in two ways. Firstly, we compared the BRAN nowcast habitat boundary anomaly for each month in 1994–2006 with those generated using POAMA forecasts at lead-times of 0–4 months for each month in each year (an example of BRAN and POAMA habitat maps is shown in Fig. 3). We evaluated how frequently both BRAN and POAMA latitude anomalies at each lead-time were north or south of the monthly climatological location of BRAN and POAMA habitat boundaries, respectively. Secondly, POAMA habitat forecasts were compared with persistence habitat forecasts (based on BRAN habitat nowcasts), as a minimum skill test.

## Results

### SBT habitat nowcast comparisons

There is good agreement between the SynTS and BRAN SBT habitat nowcast values for the period 1994–2006, with normalized RMS difference values of 0.116° and 0.095° latitude for the northern buffer and northern core, respectively. Variability of the core and buffer habitat zones about their climatology, based on the SynTS nowcasts, is approximately 1°–2° of latitude for 1994–2006 (Fig. 4a). The variability in the buffer boundary location (Fig. 4c) is greater than that of the core boundary (Fig. 4b). The BRAN nowcasts of the core habitat boundaries are shifted slightly to the south (indicating colder water) of the SynTS climatology (Fig. 4d), and again the variability in the buffer location (Fig. 4f) is greater than for the core (Fig. 4e). In summary, the overall magnitude of the deviations of the monthly BRAN habitat boundary nowcasts from the SynTS daily climatology are generally small, establishing the suitability of the BRAN nowcasts for use as the benchmark for skill assessment of POAMA habitat forecasts at different lead-times.

### POAMA ocean temperature forecast skill

The skill of POAMA forecasts of heat content anomalies of the upper 100 m in the East Australian region, when using BRAN as observations, is shown for each month of May–November 1993–2006 (Fig. 5), and shows the model is potentially useful. Model skill is highest at lead-time 0 months and

decreases with increasing lead-time for all months shown. At lead-time 0 months, skill is highest south of 36°S and east of 163°E for all months, with areas of low skill confined mostly around 32°S. This low skill is most likely a result of high variability in this region owing to the EAC and the associated intense eddy activity (Tomczak and Godfrey 1994), which cannot be resolved by the model. The months May, June, and July seem to have higher skill than those later in the season at all lead-times shown, which may also be linked to seasonal variations in EAC activity. As lead-time increases, areas of low skill extend further offshore (Fig. 5), although these areas are outside the usual region fished by the ETBF fleet.

### POAMA habitat forecasts

POAMA forecasts of core and buffer habitat boundaries, together with deviances from the operational daily climatology, are shown for 1994–2006 (Fig. 4). Predictions of the core and buffer habitat boundaries are shifted to the south compared with the daily operational climatology (Fig. 4g). The variability in the POAMA predicted core and buffer locations is similar (Fig. 4h), although overall deviation from the operational climatology is greater for the POAMA buffer boundary forecasts (Fig. 4i).

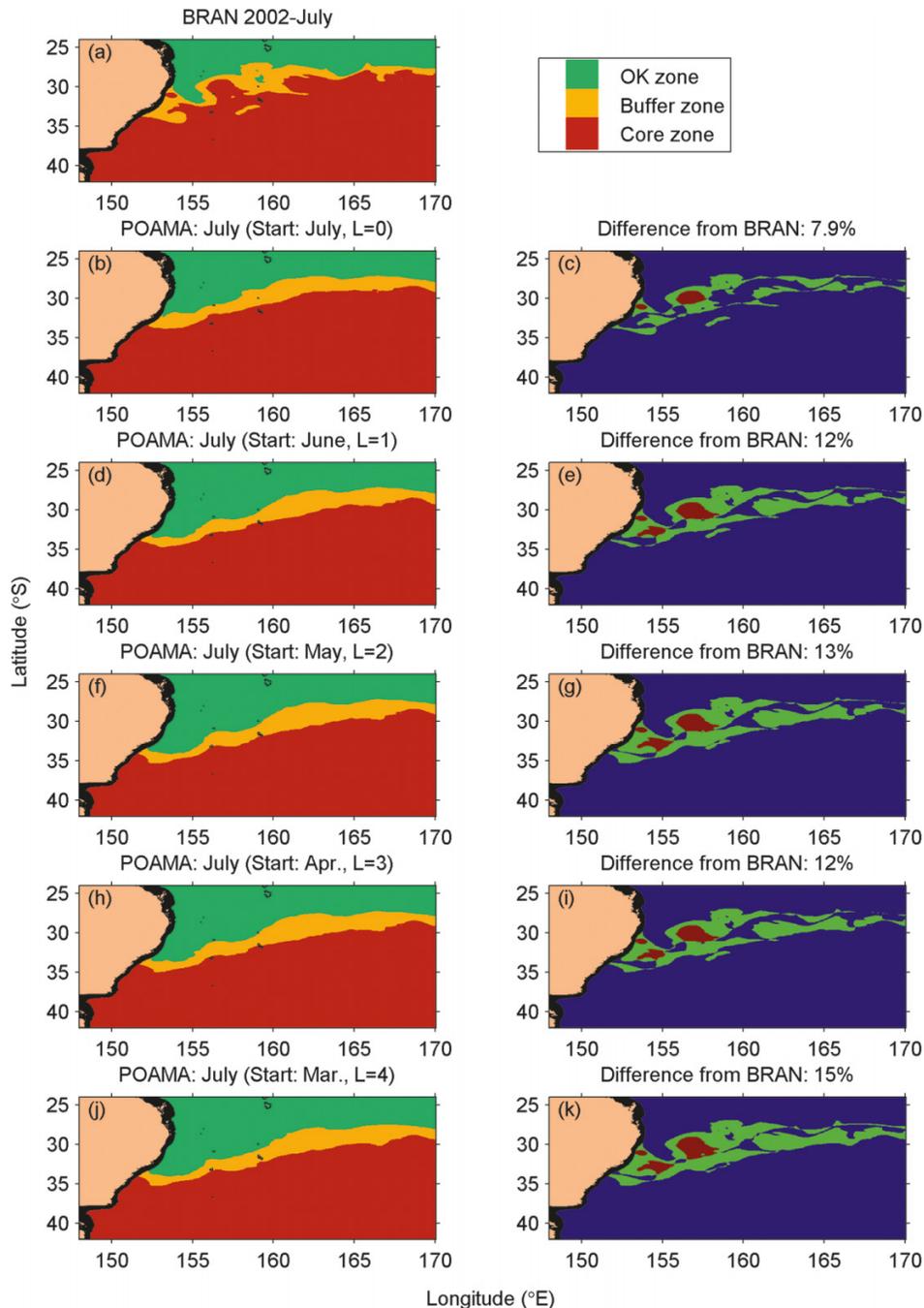
The deviations of the POAMA core zone boundary from the BRAN nowcast values for each month of 1994–2006 at different lead-times are summarized (Fig. 6). Early in the fishing year (May) the core habitat for SBT is generally to the south of the region, then extends northwards in the austral winter before retracting to the south again into summer (Fig. 1c). There is a slight seasonal signal to the deviances in the location of the POAMA core zone boundaries for all lead-times. POAMA temperature inputs have been bias corrected using BRAN climatology, therefore these deviances are most likely due to the nonlinearity of the statistical habitat model. The POAMA habitat predictions in May tend to become slightly positive at the lead-times of 3 and 4 months, indicating that POAMA habitat forecasts occasionally predicted the core boundary slightly north compared with the BRAN nowcasts (Fig. 6).

In June, the deviance tends to be positive at all lead-times, indicating that the core boundary is often forecast further north than in the BRAN nowcasts, whereas for July and October, the deviance is small. The deviance does not increase markedly for increasing lead-times, suggesting that the POAMA forecast is potentially useful out to a lead-time of 4 months, based on this analysis (Fig. 6); however, forecast skill does deteriorate regionally (Fig. 3).

Of particular interest to fishers and managers is whether the boundaries of the habitat zones can be forecast as being further north or south of the long term average location for that time of year (i.e., north or south of the climatology). Calculating the frequency with which POAMA forecasts of habitat boundaries agreed with BRAN habitat nowcasts during 1994–2006, i.e., both boundaries either north or south of the climatological location, showed that at lead-times of 0–4 months, the agreement between the location of boundaries ranged from 76% to 68% for the core zone at lead-times of 0 and 1–3 months, respectively (Fig. 7).

This agreement was lower for the more variable buffer zone, ranging from 66% to 51% agreement at lead-times of 1 and 3 months, respectively (Fig. 7). Using only the upper and

**Fig. 3.** (a) BLUElink Ocean Reanalysis (BRAN) nowcast and (b, d, f, h, and j) predictive ocean atmosphere model for Australia (POAMA) habitat forecasts of southern bluefin tuna (SBT) habitat zones for July 2002 at lead-times of 0–4 months. (c, e, g, i, and k) Difference in POAMA habitat maps for each lead-time compared with the BRAN nowcast. Blue indicates agreement in habitat classification, green indicates a difference of one habitat type (e.g., core instead of buffer), and brown indicates a difference of two habitat types (e.g., core instead of OK).

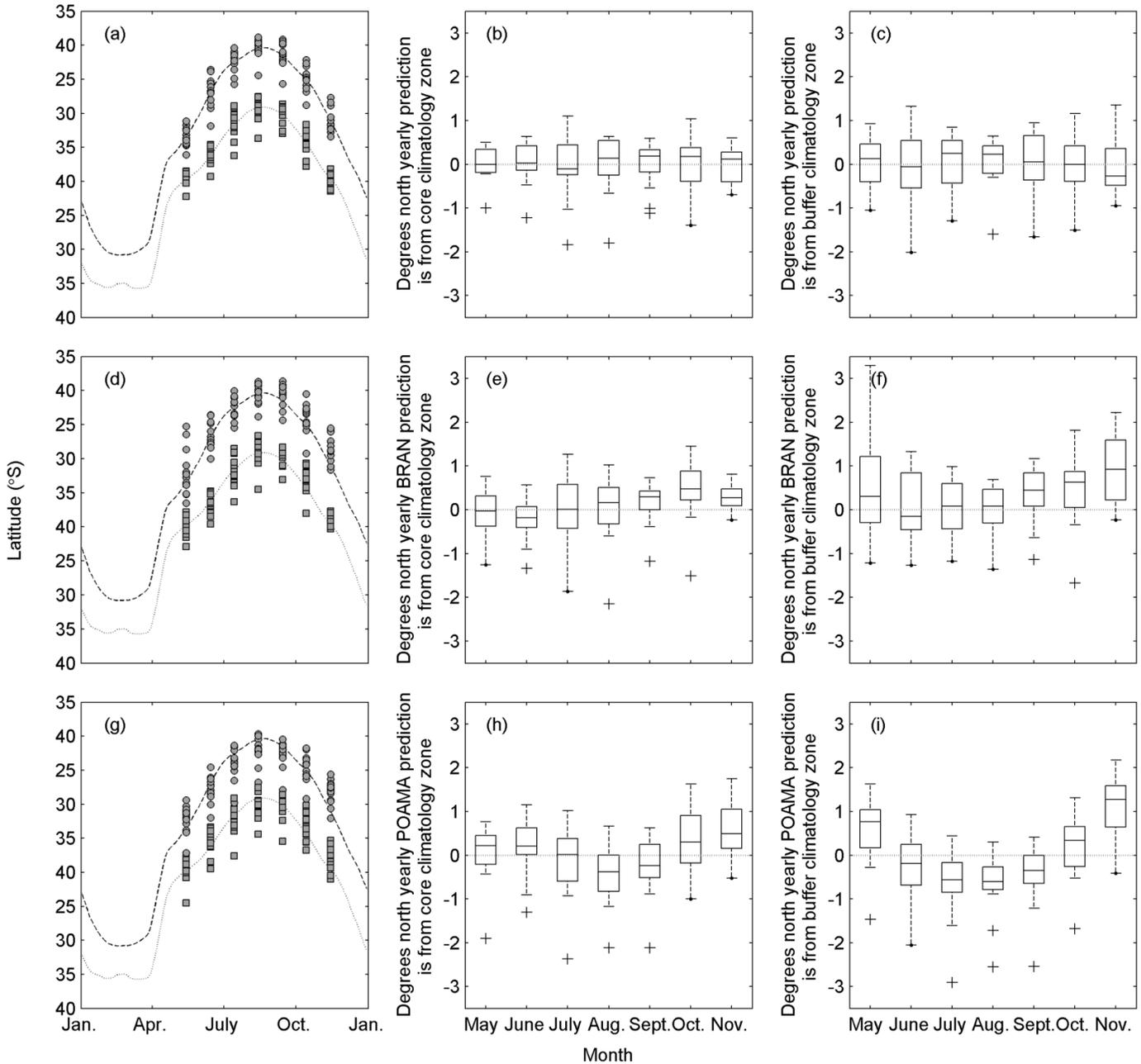


lower quartiles of the POAMA forecasts (i.e., the 25% of most northern and 25% of most southern), agreement with the subsequent observation is even greater at lead 0 for the core (89%) and buffer (88%), and declines to 83% and 81%, respectively, at lead 1, 78% and 81% at lead 2, 83% and 83% at lead 3, and to 80% and 80% at lead 4. The location of the boundaries north or south of the average locations highlights the interannual variability in the location of the zones and the

benefits of a using a dynamic forecast over a climatological forecast in those years.

The skill of model predictions in predicting the northern boundaries of the core and buffer zones was also compared with that of persistence forecasts. The skill of the POAMA forecast of the latitude anomaly for the core habitat boundary was high and declined over time, but importantly, was higher than the BRAN persistence forecast for all months at all leads

**Fig. 4.** Seasonal cycle in the location of southern bluefin tuna (SBT) habitat boundaries for 1994–2006. (a) Operational monthly habitat boundary nowcasts and deviations from the daily operational climatology for (b) the northern core and (c) northern buffer zones. (d) BLUE-link Ocean Reanalysis (BRAN) monthly habitat boundary nowcasts and deviations from the daily operational climatology for (e) the northern core and (f) northern buffer zones. (g) Predictive ocean atmosphere model for Australia (POAMA) monthly habitat boundary forecasts at lead-time 0 months and deviations from the daily operational climatology for (i) the northern core and (j) northern buffer zones. The operational habitat boundary climatologies for the northern core and northern buffer boundaries are depicted as dotted and dashed lines, respectively, in (a, d, and g). Box and whisker plots show the median, upper and lower quartile, with whiskers at the each end of the box to show the extent of the rest of the data. Outliers (pluses) are data with values beyond the ends of the whiskers.



(Fig. 8). For the more variable buffer habitat, POAMA forecast skill is similar to that of persistence forecasts at short lead times though higher for long lead times. If the skill of climatological forecasts were plotted on this figure, the line would be at zero for all lead-times, as we are assessing the skill of forecasts to determine whether a year varies from climatology or not. Thus, if we had only today’s operational habitat nowcast and assume that this habitat location would

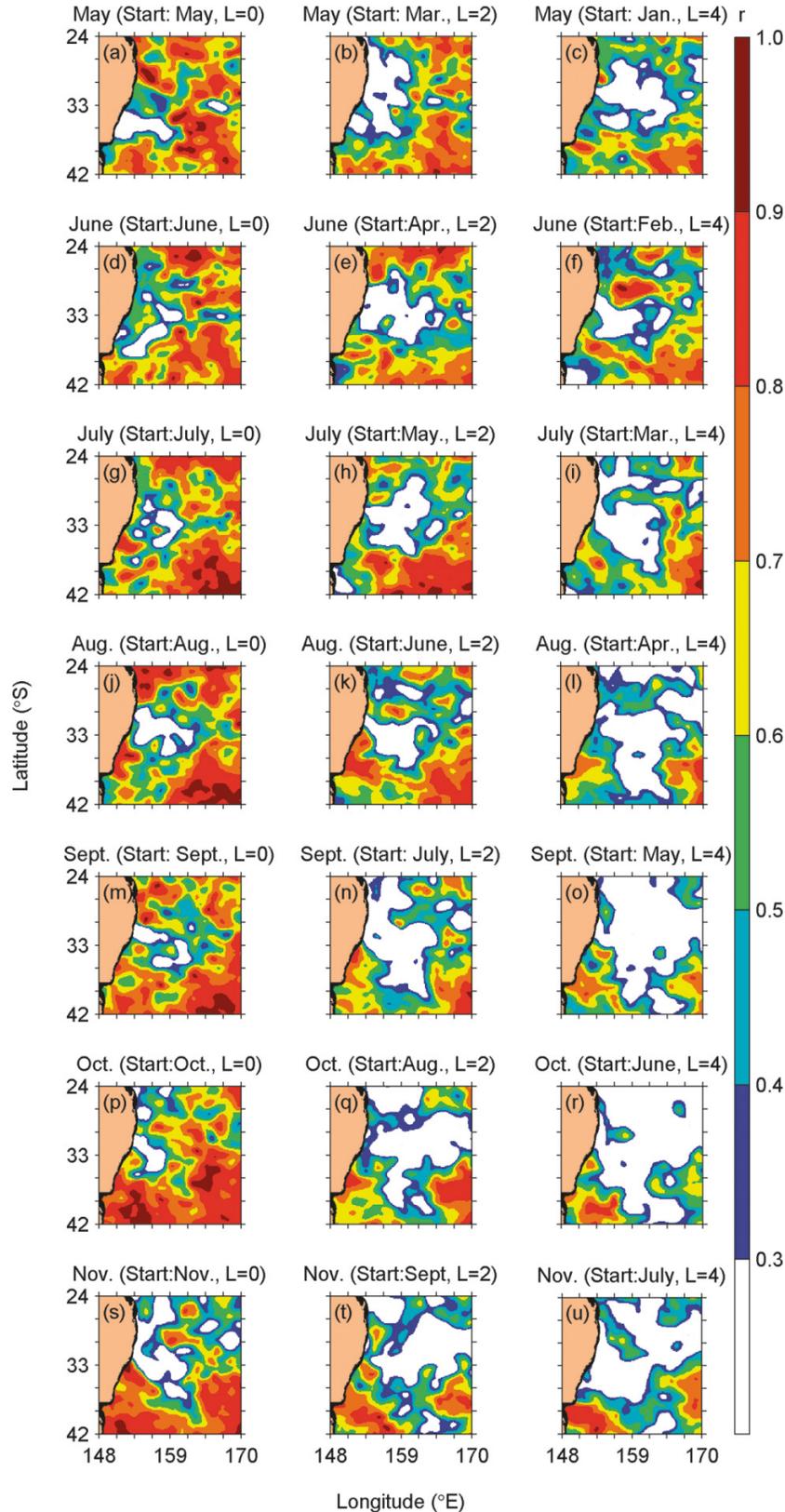
not change in the next 4 months, the results show that the model gives additional information above that assumption: the model has useful skill.

**Discussion**

The environment-based real-time prediction of SBT habitat for dynamic spatial management is one of the only examples

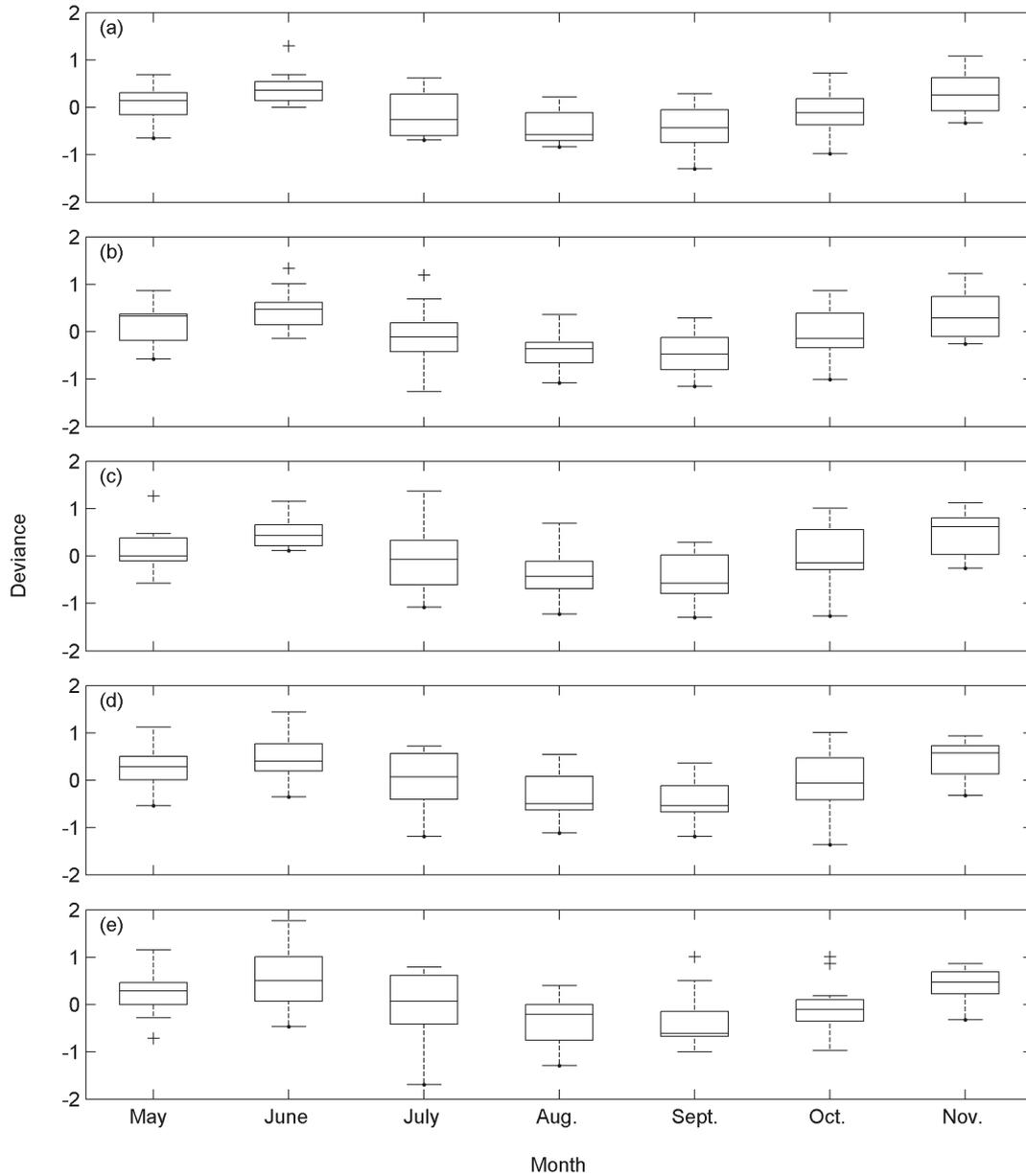
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**Fig. 5.** Skill of the predictive ocean atmosphere model for Australia (POAMA) forecasts of heat content anomalies of the upper 100 m in eastern Australia waters for (a–c) May, (d–f) June, (g–i) July, (j–l) August, (m–o) September, (p–r) October, and (s–u) November 1993–2006 at lead-times = 0 months (first column), 2 months (second column), and 4 months (third column). Significant correlations are shaded ( $r \geq 0.3$  is significant at  $p = 0.15$ ; Student's  $t$  test,  $n = 14$  years).



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**Fig. 6.** Monthly predictive ocean atmosphere model for Australia (POAMA) habitat predictions for all years (1994–2006) for lead-times of (a) 0, (b) 1, (c) 2, (d) 3, and (e) 4 months. Here the deviance is the difference between the location of the POAMA forecast core boundary and the BLUElink Ocean Reanalysis (BRAN) nowcast core boundary. Box and whisker plots show the median, upper and lower quartile, with whiskers at the each end of the box to show the extent of the rest of the data. Outliers (+) are data with values beyond the ends of the whiskers.



in the world where management uses such information (Hobday et al. 2009), although several voluntary schemes exist (e.g., Howell et al. 2008). Over time, managers in the Australian fishery have updated management lines more often, and used more complex lines to manage the fishery (Hobday et al. 2010). Additional benefit to fishers and managers could be obtained if information about future ocean conditions and distribution of fish habitat was available, allowing planning for the coming months. The overall purpose of this study was to examine whether a dynamic seasonal ocean–atmosphere model could offer useful forecasts, compared with a climatological forecast provided by the operational SynTS system.

Comparisons of BRAN habitat nowcasts with those from

the SynTS habitat system, showed a high degree of agreement, allowing the use of BRAN nowcasts as observations for validation of POAMA forecasts. When POAMA habitat predictions were compared with BRAN nowcasts for different lead-times, POAMA was able to correctly predict boundary locations that were north or south of the average climatological positions for up to 70% of the months, out to lead-times of 4 months. The predictive agreement was even greater when forecasts in the upper and lower quartiles only were considered, with agreement above 80% for most lead-times (not shown). Although the forecast skill of the model declined regionally with lead-time, it was consistently higher or similar to that of persistence forecasts for all leads.

Although the spatial resolution of the POAMA model is coarse compared with ocean reanalysis products, the model was effective in predicting the distribution of the SBT habitat. Even at a lead-time of 4 months, the percentage agreement between the POAMA forecast of core boundary locations and operational nowcast was still well above 50% (i.e., >68%), with higher skill for core zone predictions, a seasonal forecast could be useful to fishers and managers. POAMA both forecasts and skillfully predicts the variability about the climatological mean position of SBT habitat boundaries, i.e., how current conditions differ from those in other years, which is key for adaptive fishery management.

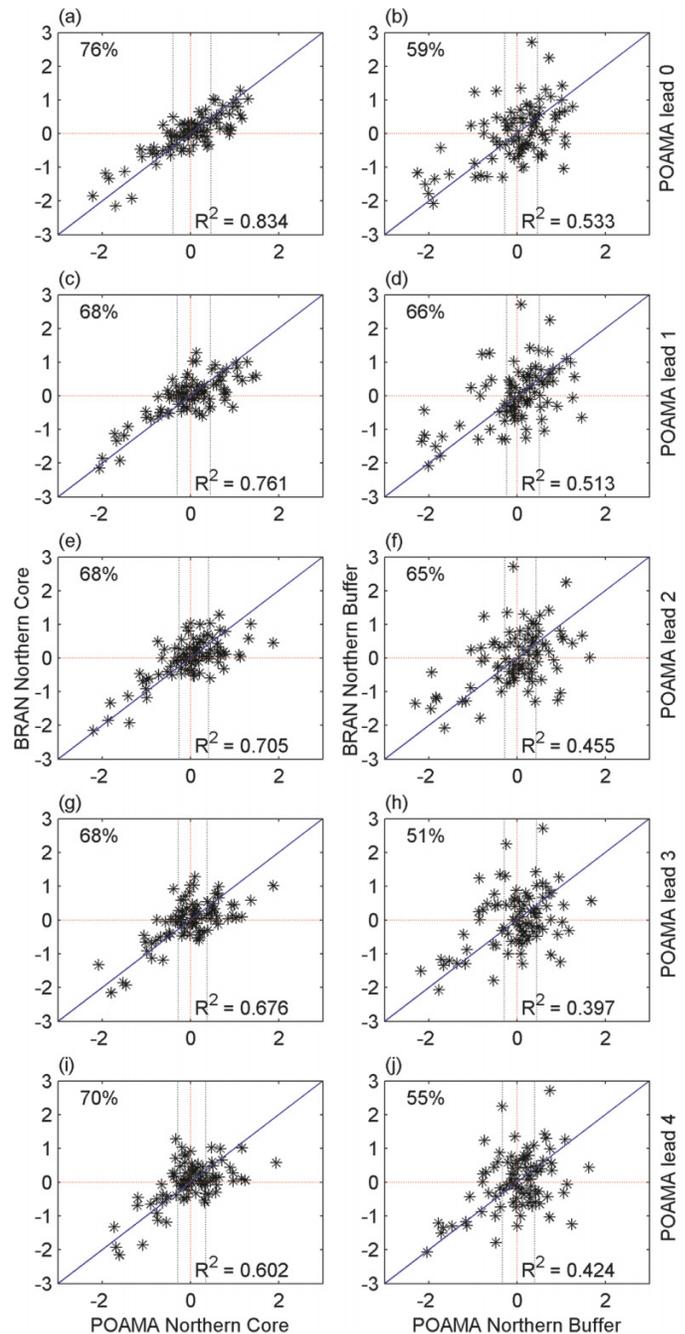
The metric we used to compare models was a simple summary of mean latitude of a habitat boundary. When the habitat boundary slopes from southwest to northeast, this summary value reflects the average latitude of the boundary, yet can conceal information on coastal features such as the southward penetration of the EAC. While this is the approach used for ongoing operational management, a more sensitive measure based on the total spatial agreement, could be developed in future to compare habitat predictions.

The study region is an oceanographically complex area, with much mesoscale structure. The location of SBT habitat along the east coast of Australia is dominated by the EAC, which has both a strong seasonal cycle and interannual variability in the cycle (Ridgway and Godfrey 1997), rendering habitat predictions both valuable and challenging. This challenge was illustrated in the differing forecast skill by month in this region. Improved forecast capability even in this complex region may be achieved by calibration, where POAMA predictions of large scale drivers such as ENSO, which generally have high skill, and statistical relationships between those and the region may be used (Wang et al. 2008; Spillman et al. 2010b). Downscaling may also be a useful technique to enhance forecasts at regional and local scales.

Forecast calibration and downscaling may be useful for a range of other fish species in eastern Australia if data on habitat preference is available, such that a habitat model could be constructed (e.g., yellowfin tuna; Hartog et al. 2011). Tuna habitat models exist for the Mediterranean Sea (Druon 2010) and the Gulf of Mexico (Teo et al. 2007), and could be used with suitable ocean models to generate useful forecasts for fisheries management. In other regions of higher POAMA skill, more accurate seasonal forecasts may also be available at longer lead-times, an exciting possibility for marine managers. Coupling the physical model to the biological habitat model to allow forecasting opens up a range of options for managers and fishers, which could enhance fishery sustainability. In eastern Australia, these fisher options include forward planning of relocation of boats and crew to ports along the coast, while for managers, information on the future placement of spatial restrictions can assist with planning deployments of fishery observers and ease ongoing tensions between management and industry.

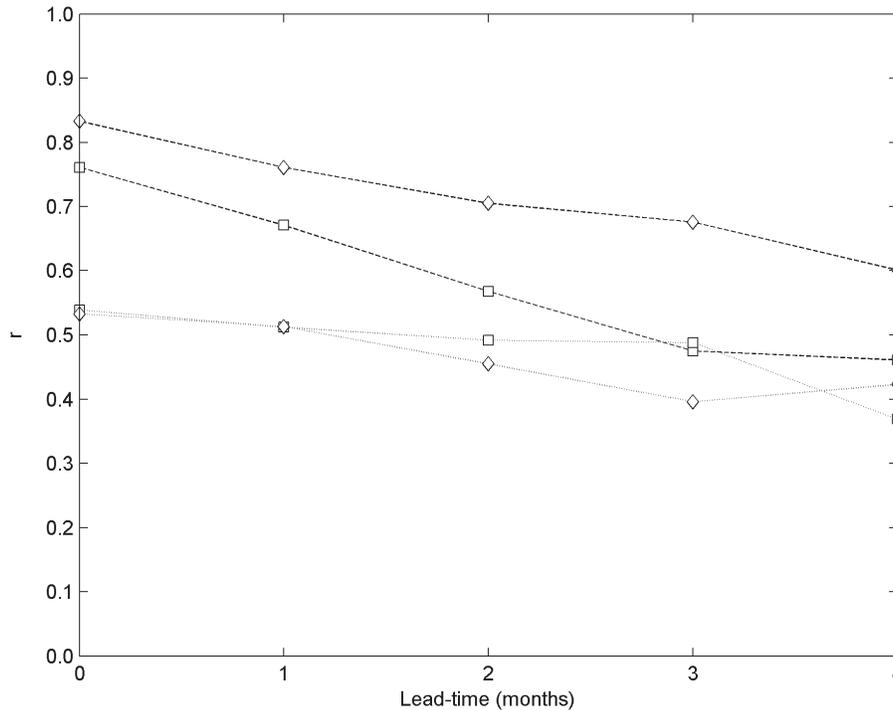
Currently the predictions of habitat location using the operational SBT habitat model are delivered to management every 2 weeks via email. Managers are interested in using the POAMA seasonal forecast (T. Timmis, Australian Fisheries Management Authority, Canberra, Australia, personal communication 2010), but there are likely to be implementation challenges in delivery of real-time seasonal forecasts.

**Fig. 7.** Comparison of the predictive ocean atmosphere model for Australia (POAMA) habitat latitude anomalies with the BLUElink Ocean Reanalysis (BRAN) habitat latitude anomalies for the core zone (first column) and buffer zone (second column) for lead-times of (a, b) 0, (c, d) 1, (e, f) 2, (g, h) 3, and (i, j) 4 months for May–November 1994–2006. The percent sign agreement (upper left in each panel) is the percentage of POAMA forecasts that were north or south of POAMA climatology when BRAN nowcasts were also north or south of the BRAN climatology. The 1:1 line is shown on each panel. Broken lines represent the zero lines and upper and lower quartile lines for the POAMA forecasts at each lead.



Currently other operational POAMA products such as coral bleaching forecasts are updated online daily (e.g., Australian Government Bureau of Meteorology 2011). This has been a

**Fig. 8.** Forecast skill of the predictive ocean atmosphere model for Australia (POAMA, diamonds) and persistence forecasts (squares) for the location of the northern boundaries of the core (dashed lines) and buffer (dotted lines) zones for May–November 1994–2006 at lead-times 0–4 months. Skill is calculated as the correlation between the forecast (POAMA or persistence) and the observed conditions (BLUElink Ocean Reanalysis (BRAN) nowcast) at each lead-time.



useful and convenient approach, allowing for regular updates of forecasts and proactive monitoring of the upcoming season. A similar approach is planned for SBT habitat forecasts, coupled with some initial training for managers on how best to interpret the forecasts. An example that might be provided to managers is shown in Fig. 1c, with the forecasts plotted on the operational climatology.

It is important to note that underlying all predictions and forecasts are the SBT habitat preferences derived from PSAT data. These may have potential shortcomings in terms of predicting fish presence and hence catchability. For example, habitat models based only on electronic tag data reflect both feeding and nonfeeding behavior. Feeding is clearly a critical element if the fish is to take a bait and be captured by a fishery. Ward and Myers (2005) show that depth of capture did not match the depth distribution obtained from archival tags for four species (but not including SBT), thus habitat preferences weighted by time at depth as in our habitat model (Hobday and Hartmann 2006) may not accurately reflect feeding opportunities. However, previous work has shown our operational model does generate predictions that match the SBT catch distribution (Hobday et al. 2010).

Given that ocean conditions and the distribution of fishes are changing on the east coast of Australia (Poloczanska et al. 2007; Last et al. 2011) and are predicted to change further in future (Hobday 2010), flexibility in management will be important to ensure the sustainability of the ETBF fishery. While long-term climate forecasts have considerable variation, and may not yet be useful in guiding operational fisher and management decisions (Hobday and Poloczanska 2010), using seasonal forecasting represents a valuable adaptation

step. Marshall (2010) showed that fishers that used seasonal forecasting had greater climate resilience. Greater confidence in future conditions through the use of seasonal and longer term forecasting can lead to improved management, greater flexibility, and increased confidence in business decision making by a range of stakeholders (Marshall 2010), leading to more sustainable fishing practices.

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