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Seasonal forecasting for decision support in marine fisheries and aquaculture

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ABSTRACT

The production of marine protein from fishing and aquaculture is influenced by environmental conditions. Ocean temperature, for example, can change the growth rate of cultured animals, or the distribution of wild stocks. In turn these impacts may require changes in fishing or farming practices. In addition to short-term environmental fluctuations, long-term climate-related trends are also resulting in new conditions, necessitating adjustment in fishing, farming and management approaches. Longer-term climate forecasts, however, are seen as less relevant by many in the seafood sector owing to more immediate concerns. Seasonal forecasts provide insight into upcoming environmental conditions, and thus allow improved decision making. Forecasts based on dynamic ocean models are now possible and offer improved performance relative to statistical forecasts, particularly given baseline shifts in the environment as a result of climate change. Seasonal forecasting is being used in marine farming and fishing operations in Australia, including wild tuna and farmed salmon and prawns, to reduce uncertainty and manage business risks. Forecast variables include water temperature, rainfall and air temperature, and are considered useful up to approximately 4 months into the future, depending on the region and season of interest. Species-specific habitat forecasts can also be made by combining these environment forecasts with biological habitat preference data. Seasonal forecasts are useful when a range of options are available for implementation in response to the forecasts. The use of seasonal forecasts in supporting effective marine management may also represent a useful stepping stone to improved decision making and industry resilience at longer timescales.

Key words: climate variability, prawn, Predictive Ocean Atmosphere Model for Australia, risk management, salmon, tuna

INTRODUCTION

Marine food production from fisheries and aquaculture plays an important role in many regional and national economies and provides an important source of protein for people worldwide (Brander, 2007; Allison *et al.*, 2009; Merino *et al.*, 2012). With projections of human population growth approaching 10 billion by 2050 and considerable challenges in increasing the harvest from wild fisheries (Rice and Garcia, 2011; Cheung *et al.*, 2012), development of aquaculture is seen as critical for future human food security (Bell *et al.*, 2009; Merino *et al.*, 2012). Continued sustainable harvest of wild stocks must also continue, which requires improved management approaches and economically efficient fishing and farming strategies (Worm *et al.*, 2009; Branch *et al.*, 2011; Callaway *et al.*, 2012), particularly in areas with rapidly changing environments (Melnychuk *et al.*, 2014).

Just as in terrestrial food production, fisheries and aquaculture production is subject to environmental stresses that result in considerable interannual variation in production. Ocean temperature, for example, can impact the growth rate of cultured and wild animals (Thresher *et al.*, 2007; Neuheimer *et al.*, 2011; Callaway *et al.*, 2012), and the distribution of wild stocks (Heath *et al.*, 2012; Jung *et al.*, 2014; Pinsky and Fogarty, 2012). In addition to short-term environmental fluctuations, long-term climate-related trends are also resulting in changing conditions in many marine regions (Hobday and Pecl, 2014). Given projected long-term climate impacts on seafood production at regional (Brown *et al.*, 2009), national (Callaway *et al.*, 2012; Bell *et al.*, 2013) and global (Cheung *et al.*, 2010; Merino *et al.*, 2012) scales, adaptation in

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fishing, farming and management practices is required to minimize losses in fisheries and aquaculture production in some regions (Hobday *et al.*, 2008; Salinger and Hobday, 2013), whereas maximizing opportunities in others (Brander, 2007; Hobday *et al.*, 2008; Cochrane *et al.*, 2009; Bell *et al.*, 2013).

One way of improving performance of seafood businesses and managers is through the provision of environmental forecasts. Management responses could be implemented ahead of time to reduce impacts that result from unfavorable conditions and maximize opportunities when optimal conditions occur. Just as weather forecasts influence decision making at short timescales, such as when and where to fish (e.g., Dell *et al.*, 2011), environmental information on longer timescales may also be useful to planning. While there are a range of obstacles that can limit delivery of such information (e.g., Sarachik, 2000), attention to engagement with stakeholders now receives much greater priority. For example, considerable attention has been directed to the development and dissemination of climate projections relevant to fisheries (e.g., Cheung *et al.*, 2010; Hobday, 2010; Bell *et al.*, 2011) and aquaculture (Battaglene *et al.*, 2008; Hobday and Lough, 2011; Merino *et al.*, 2012) out to the end of the century. Climate forecasting at these timescales is considered useful for some infrastructure, coastal planning and long-term industry changes (Hobday *et al.*, 2008). However, such long-term climate forecasts are seen as less relevant by many in the seafood sector given a wide range of more immediate concerns, such as short-term environmental conditions, labor costs, market pressures and environmental regulation (Nursey-Bray *et al.*, 2012; Fleming *et al.*, 2014). Thus, improved performance of fisheries and aquaculture under changing environmental conditions may be achieved by focusing on a more relevant timescale to these users (Fig. 1).

At the other end of the spectrum to climate-scale projections is weather forecasting, which is widely used for planning activities on timescales from hours to days (Fig. 1). Experienced individuals often use qualitative forecasting for informing decision making: a simple look skyward can allow a forecast about the potential for rain in the coming hours. The main source of information at this timescale, quantitative forecasts, is issued by meteorological services and can support seafood production and management planning at 1–7 day timescales.

Between these two extremes, is seasonal forecasting, which aims to deliver information at a timescale of weeks to months (e.g., Spillman and Alves, 2009). Seasonal marine forecasts, as for agriculture, provide information regarding future environmental conditions, and thus allow improved decision making for a range of these marine industries. It is important to emphasize that the effective use of seasonal forecasts requires proactive and responsive management with a range of strategies that can be implemented on the basis of the forecasts (Fig. 1) (Sarachik, 2000). In aquaculture, for example, there are operational decisions made at a range of timescales, some of which could be modified in response to future environmental information (Fig. 1). Sea temperatures, for example, are linked with salmon health and disease prevalence (Battaglene *et al.*, 2008). Advance warning of potentially warm summers or cold winters may give farmers time to respond and adapt feeding or stocking strategies to maximize production under particular conditions. Likewise, fishery managers may implement particular management strategies if interactions between target and bycatch species are suggested to increase under environmental conditions forecasted for the upcoming season (e.g., Hartog *et al.*, 2011).

Here, we show how seasonal forecasting is being used in a range of marine farming and fishing operations in Australia, including wild tuna and farmed salmon and prawns, to reduce uncertainty and manage

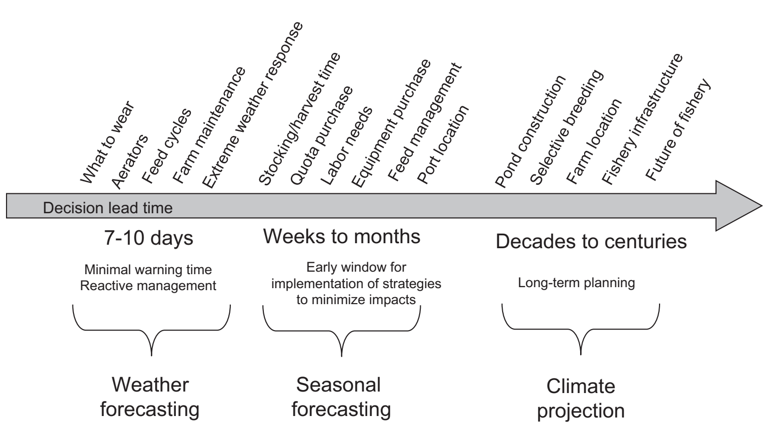


Figure 1. Information on future environmental conditions can be delivered at a range of timescales. The appropriate timescale can depend on the period until the decision must be implemented, or the time at which the environmental conditions are expected to occur.

business risks. The use of seasonal forecasts in supporting effective, proactive marine management may also provide a useful stepping stone to improved decision making and industry resilience at longer timescales.

The why and how of seasonal forecasting

To many in the seafood production or management sectors, climate variability is just 'business as usual' (Nursey-Bray *et al.*, 2012). However, merely coping with climate variability represents a responsive and often conservative management approach (Hodgkinson *et al.*, 2014). This is likely to be less cost-effective than proactive management, where information about future conditions is integrated into planning activities, both helping to minimize impacts in poor seasons and capitalize on opportunities in good seasons.

Seasonal forecasts can be based on statistical or dynamical quantitative approaches. Statistical methods typically use historical data as the basis of estimating future outcomes, and can range from the simple climatological forecasts to complex autoregressive multi-parameter models. Statistical relationships may exist between atmospheric or oceanic indicators and local variables, or between local variables at two points in time, and thus form the basis for prediction. While statistical forecast methods can often be quite skilful, dynamic ocean model forecasts do not assume a constant climate baseline and can offer improved performance under climate change (Spillman, 2011).

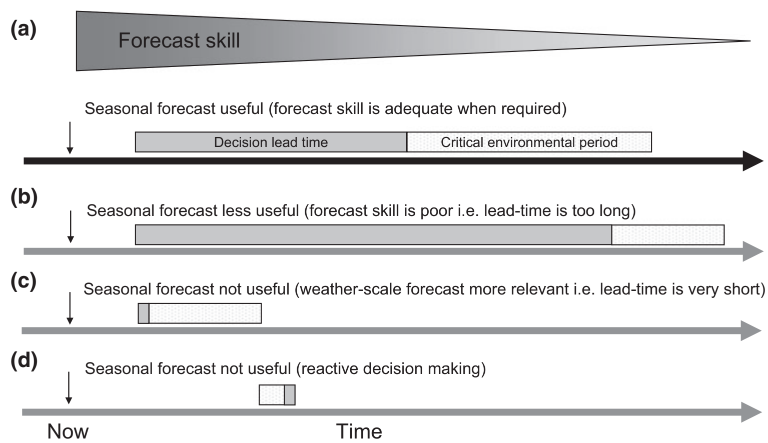
Seasonal forecasting methods for marine applications are based on dynamical global atmospheric and oceanic circulation models. In each of the case studies described below, the Australian Bureau of Meteorology (BOM) seasonal forecast model, referred to as the Predictive Ocean Atmosphere Model for Australia (POAMA), was used. POAMA is a state-of-the-art seasonal forecast system based on a coupled ocean/atmosphere model and ocean/atmosphere/land observation assimilation systems (Spillman *et al.*, 2012). Extensive analyses have been done of the capability of the POAMA system for regional forecasting of climate around Australia (e.g., Spillman and Alves, 2009; Marshall *et al.*, 2012; Spillman *et al.*, 2012; White *et al.*, 2013). Seasonal forecasts from POAMA of high-risk conditions in marine ecosystems can be very useful tools for managers, allowing for proactive management responses. For example, POAMA is currently used to produce operational real-time forecasts for coral bleaching risk on the Great Barrier Reef (Spillman and Alves, 2009; Spillman *et al.*, 2012). These bleaching forecasts provide an early warning of potential bleaching conditions prior to summer, which allows reef managers to both focus monitoring programs and implement strategies to minimize bleaching damage, as well as to brief government (Maynard *et al.*, 2009).

Seasonal forecasts are potentially useful for other marine sectors, such as fisheries and aquaculture, in situations where (i) there is an action that must be planned in advance (e.g., ordering a new feed mix) and (ii) the forecast skill remains useful at the point of time in future when the action must be implemented (e.g., time when feed mix is given to the cultured animals) (Fig. 2).

A first step in developing a seafood industry forecasting application is to assess model skill for the environmental variables of interest. Forecast variables used in our examples include water temperature (at surface and at depth), rainfall and air temperature, and are considered useful up to 4 months into the future, depending on the region and season of interest. Model skill can be assessed by correlating historical model mean values with historical observed values in both space and time using Pearson's Correlation Coefficient (Spillman and Alves, 2009; Spillman *et al.*, 2012), or probabilistically by assessing the forecast hit-rate (correct versus incorrect forecasts) (Spillman and Hobday, 2014). One primary criterion is that a sufficient period of data is required to assess the performance and accuracy of forecasts over the historical period. In the case of ocean temperatures, satellite sea surface temperatures or observational data re-analyses (e.g., PEODAS; Yin *et al.*, 2011) can be used. Other historical datasets can be used for variables such as air temperature and rainfall (e.g., Bureau of Meteorology Australian Water Availability Project AWAP; http://www.bom.gov.au/climate/maps/). In the absence of such data, forecasts can still be made, but the quality cannot be verified by historical analysis.

Once the skill of the model forecasts has been assessed, a second step may be required to relate the regional forecast information to a local scale, such as the location of aquaculture sites. Statistical downscaling may be used where a significant relationship between regional conditions and local conditions is established. For example, there is a strong relationship between regional ocean temperatures around Tasmania and coastal salmon farm temperatures. Forecasts of regional ocean temperature can be provided by POAMA for several months into the future which can then be used as input to forecast summer farm temperatures (Spillman and Hobday, 2014). Alternatively POAMA forecasts can be used as input into statistical habitat models to give sophisticated probability maps of habitat distribution e.g., southern blue fin tuna (Hobday *et al.*, 2011). In some cases regional forecast

Figure 2. The utility of seasonal forecasting depends on the timing of both the management decision to be made and that of the critical environmental period affecting the decision, in conjunction with whether the skill of the forecast is adequate at that time. When the lead-time required to make and implement a decision (shaded portion of the horizontal bar) is such that the forecast skill for the critical environmental period is adequate, a seasonal forecast may be useful (a). When the lead-time required is too long, forecast skill during the critical environmental period may decline and be less than adequate, so a seasonal forecast will be less useful (b). When the lead-time required is very short, weather forecasting may be more appropriate (c). When the management decision is made after the critical environmental period occurs, forecasting is not useful (d).

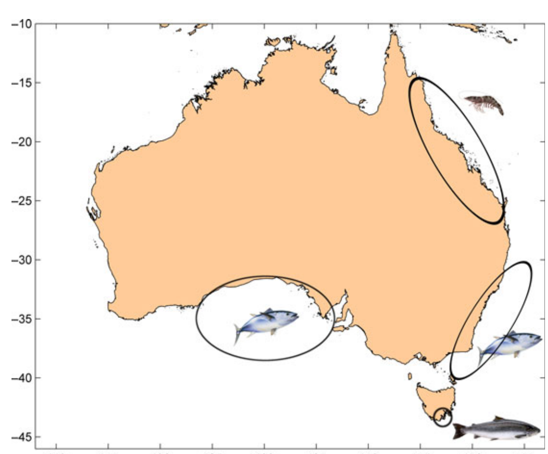


information directly from POAMA is the most useful for industry and so no extra statistical modeling is required.

SEASONAL FORECASTING APPLICATIONS IN AUSTRALIAN SEAFOOD SECTORS

Here we describe four examples of seasonal forecasts developed to aid Australian fisheries managers, fishers and fish-farmers; two are aquaculture applications and two are wild fishery applications (Fig. 3, Table 1). In general, as aquaculture is location based, aquaculture forecasts have been for environmental variables only (e.g., water temperature at some time in the future), statistically downscaled to a region or site of interest, and delivered with estimates of forecast skill. Applications to wild fisheries have involved delivering either environmental forecasts or habitat-based forecasts (obtained by projecting species-specific habitat preferences onto environmental forecasts; see Example 2 below), and assessing the skill of these forecasts. The examples presented are intended to illustrate the range of seafood sectors utilizing seasonal forecasting, and generalize some insights from these examples.

Figure 3. Forecasts are being generated for a range of species in several regions of Australia, including wild tuna fisheries in eastern and southern Australia, and prawn and salmon aquaculture in Queensland and Tasmania, respectively. Salmon image courtesy of Peter Whyte and CSIRO, tuna and prawn images courtesy of CSIRO.



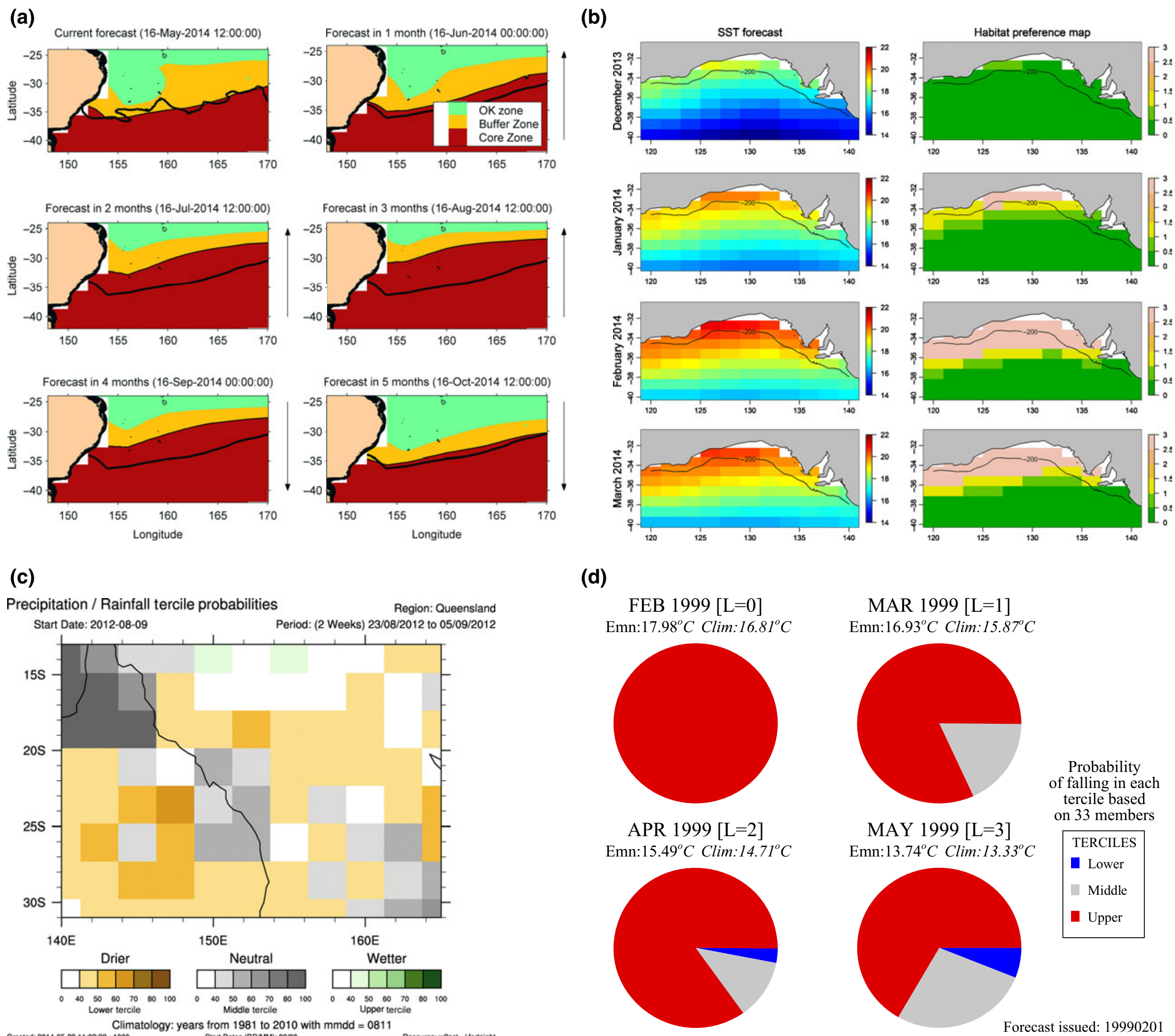
Example 1: Southern bluefin tuna in eastern Australia

Southern bluefin tuna (SBT, *Thunnus maccoyii*) is a quota-managed species, a proportion of which makes annual winter migrations to the Tasman Sea off south-eastern Australia (Fig. 3). During this period it interacts with a year-round tropical tuna longline fishery (Eastern Tuna and Billfish Fishery, ETBF). Fishery managers seek to minimize the bycatch of SBT by commercial ETBF longline fishers with limited or no SBT quota through spatial restrictions (Hobday and Hartmann, 2006). A temperature-based SBT habitat model has been used since 2003 to provide managers with an estimate of tuna distribution upon which they can base their decisions about placement of management boundaries. Data on adult SBT temperature preferences are collected using pop-up satellite archival

Table 1. General characteristics of the seasonal forecasting applications discussed in the text. All applications were co-supported by the relevant sector.

	Longline fishery – east Australia	SBT fishery – southern Australia	Prawn pond aquaculture – Queensland	Salmon coastal cage aquaculture – Tasmania
Industry annual value	A$40M	A$60M (wild catch)	A$70M	A$500M
Management issue	Southern bluefin tuna (SBT) is a quota managed species in the east Australian longline fishery – catch must be regulated	Fishers wish to know where fish are expected to be located in order to position vessels in best region to access fish	Farmers wish to optimize prawn growth and yield	Farmers want optimal conditions for salmon growth and health, and information on likelihood of sub-optimal conditions
Environmental driver	Water temperature influences distribution of SBT in region	Water temperature influences distribution of SBT in region	Prawn growth is sensitive to hot or cold pond temperatures	Water temperature linked to salmon growth and health
Management need	Mimimize non-quota catch by fishers using temperature-based predictions of SBT distribution	Improve economic efficiency of fishing operations using habitat models to predict SBT distribution	Reduce vulnerability to cool temperature & rainfall extremes	Reduce vulnerability to temperature extremes
Motivation to engage with forecasting research	Communication and extension with fishers regarding upcoming management season	Recent anomalous years of fish distribution	Recent cyclone, floods, and awareness of environmental impact	Recent warm summers, and awareness of environmental impact
Variable	Temperature	SST	Air temperature, rainfall	SST
Scale (region of interest)	100's km	100's km	m-km (ponds)	km's (lease areas)
Target season (time of concern)	Winter	Summer	Annual	Summer
Industry engagement	Phone calls and email	Fact sheet, port visit, industry co-investigator	Fact sheet, farm visit (2 rounds, scoping and feedback) industry contacts, peak body liaison	Email, meetings
Data used to support forecast product development	Scientific: tag and historical environmental data Industry: catch data for validation	Scientific: tag data, survey data Industry: historical catch, survey data	Scientific: meteorological data Industry: historical time series on pond environment, and meteorological data	Industry: historical time series on farm temperatures
Final product	Habitat forecast	Habitat forecast	Environmental forecast	Environmental forecast
Delivery mechanism	Fortnightly reports emailed to managers, (fishers advised by VMS)	Web-based updates every 2 weeks	Web-based updates every 2 weeks	Monthly emails to end users
Response option supported by habitat forecasts	Spatial zoning to regulate access by fishermen	Planning of purse-seine operations, such as where and when to move vessels	Timing of stocking & harvesting, diet, ordering supplies in advance (variety)	Freshwater bathing, diet modifications (variety)

Figure 4. Forecast examples for (a) southern bluefin tuna in eastern Australia, (b) southern bluefin tuna in southern Australia, (c) prawn farms in north-east Australia and (d) salmon farm in south-east Tasmania.



tags, and the predicted location of SBT is determined by matching temperature preferences to satellite sea surface temperature (SST) data and vertical temperature data from an oceanographic model (Hobday and Hartmann, 2006). Regular reports detailing the location of predicted temperature-based SBT habitat are produced during the fishing season when interactions with SBT occur (essentially a 'nowcast' of SBT habitat). These nowcasts have allowed managers to set zones in such a way that an unwanted catch has been reduced in proportion to the expected amount in each of the zones (Hobday *et al.*, 2010).

Since 2011, POAMA forecasts have also been provided to assist managers in this fishery (Hobday *et al.*, 2011). Ocean temperature forecasts are combined with the statistical SBT habitat model to produce predicted habitat maps for several months into the future (Fig. 4). The forecast system has skill in predicting SBT habitat boundaries out up to 3–4 months ahead (Hobday *et al.*, 2011). These habitat maps are used by managers to prepare fishers for the upcoming season and to indicate if zones will be typical or further north or south than usual for the months ahead. Habitat projections and forecasts are delivered via email to fishery managers, who then communicate the zoning decision to the fishers. The seasonal forecasts are used by managers to prepare fishers for potential restrictions that may arise further into the season, but direct management actions are based only on the habitat 'nowcast' (Hobday *et al*., 2011).

Example 2: Southern bluefin tuna in the Great Australian Bight

Southern bluefin tuna are also captured by a quota-limited purse-seine fishery in southern Australia (Fig. 3), with schools of juvenile fish caught and towed in cages back to Port Lincoln (~135°E 35°S) in the summer where they are grown and fattened before harvest some months later. Data from a large-scale archival tagging experiment conducted on juvenile SBT in the mid to late 2000s have been used to model habitat preferences of juvenile SBT off southern Australia (Appendix 11 in Basson *et al*., 2012). SST and chlorophyll-*a* levels were found to influence the distribution of SBT. In 2013, a project was initiated to forecast, first, environmental conditions that affect SBT distribution and, subsequently, habitat distribution of juvenile SBT in southern Australian waters based on findings from Basson *et al*. (2012) (Fig. 4). As POAMA is strictly a physical model and chlorophyll-*a* levels are not simulated, only SST data have been used in the environmental and habitat forecasts produced to date.

POAMA SST forecasts for southern Australia are useful up to lead-times of 2 months in the summer and 3–4 months in the winter (although fishing is in the summer only). Delivery of forecasts is via a private website to registered fishers which is updated every 2 weeks. These forecasts are being used by fishers to plan where and when to send purse-seine vessels. As the fishery is managed under a quota, which is captured every year, this application does not lead to more fish being captured, but should improve the economic efficiency of the catching operations, which is important owing to rising costs and increasing international competition in the Japanese market. Engagement with industry representatives was critical in the development of the forecast system, and is expected to provide valuable feedback after the first summer of operation (January–March 2014).

Example 3: Prawn aquaculture in Queensland

In Australia, pond-based prawn aquaculture for two main species (tiger and banana prawns) is located predominately in a narrow coastal strip of north-east Australia between Cairns and the Queensland border (~15–25°S) (Fig. 3). Farms are typically located near a tidal inlet or creek for access to a water supply to flush and fill ponds and allow salinity control. Commercial prawn farms typically consist of between 10 and 100 shallow ponds (~1.5 m deep) of ~1 ha in size. The industry is vulnerable to both extremes in temperature and rainfall and to tropical cyclones. Heavy rainfall can reduce the water quality of water supplies to the farm, particularly the first pulse of heavy falls for the season, which flush the catchment and can render the farm water supply unusable (herbicides, clay particles and harmful algal species). Heavy rainfall can also wash out roads and prevent supplies from reaching remote farms, as well as lower pond salinity below optimal levels. Temperature influences the growth of prawns and thus the timing of harvest, which is critical to delivering supply for peak market opportunities – getting it right is important for farm cash flow.

Regional POAMA forecasts of maximum and minimum air temperature, and rainfall showed forecast skill up to a season ahead, with skill of air temperature forecasts exceeding those for rainfall. Forecasts for industry sub regions are delivered via an industry-specific website (Fig. 4, http://poama.bom.gov.au/marine_mw/prawn_project.shtml). This website also points to other useful information sources for farmers including the Bureau of Meteorology forecasts for the annual tropical cyclone season and the El Nino Southern Oscillation (ENSO). In this project there were multiple farm visits, which were found to be invaluable both in designing useful forecast products and educating farmers in their interpretation. To date, farmers have used the forecast projections to plan when to stock and harvest their ponds, consider different feed mixes, and manage market expectations for the time of delivery and size of product.

Example 4: Atlantic salmon aquaculture in Tasmania

The Tasmanian salmon (*Salmo salar*) aquaculture industry has grown from establishment in 1984 to now represent Australia's most valuable seafood industry (DPIPWE, 2013). Several companies farm salmon in a range of Tasmanian locations, with south-east Tasmania accounting for up to 50% of the annual production (Fig. 3). Salmon are moved from freshwater ponds to coastal sea cages at 6–12 months of age for the final 2 years of production. While in sea cages the fish are subject to the local environmental conditions, with salmon grown in Tasmanian waters approaching their upper thermal limit in summer (Battaglene *et al*., 2008). Increases in water temperature occur seasonally owing to the warming influence of the East Australia Current (EAC) in summer, while there is also a long-term warming trend and a poleward extension of the EAC (Ridgway, 2007; Wu *et al*., 2012).

Farm-specific dynamic forecasts were first developed in 2010, focusing on surface water temperature (Table 1). Using historical farm records of water temperature to statistically downscale POAMA sea surface temperature forecasts for the region in question, Spillman and Hobday (2014) show that the forecasts have a useful skill (i.e. predictive ability) for all months of the year up to 2 months ahead. Model skill was highest when forecasting for the winter months, and lowest for December and January. The poorer performance in the summer may be as a result of the increased variability owing to the convergence of several ocean currents offshore from the salmon farming region. Forecasts are delivered to individual salmon companies via email every month during the critical summer period October to March. In response to forecasts, farm managers can implement a range of responses, including changing stocking densities, varying feed mixes, transferring fish to different locations in the farm region, implementing disease management, and modifying labor needs associated with these responses (Table 1).

DISCUSSION: LESSONS FOR SEASONAL FORECASTING IN MARINE SEAFOOD SECTORS

Information about the future will be useful if management decisions can be modified on the basis of that information. For a range of seafood industries, environmental conditions can impact on business activities and profitability, and therefore information on potential future environments is highly sought. Feedback from end users in the examples described above has shown that information about the future weather or climate conditions is useful for risk management, business planning and, if used correctly, improving overall business performance. As for coral reef managers, providing real-time seasonal forecasts (Maynard *et al.*, 2009; Spillman, 2011) can lead to better strategic management approaches for seafood industries, as long as suitable guidance in the use of forecasts is provided, particularly in the interpretation of uncertainty (Marshall *et al.*, 2011).

While most agree that future information can enhance business adaptation at a range of timescales, development of appropriate forecast tools and products is not straightforward. Our experience suggests that development of a successful and enduring forecast system has three stages: assessment of needs, forecast development and implementation (Fig. 5). Engagement with industry and/or management, as part of the first stage, is critical to define the problems that seasonal forecasting can address (see Table 1), to determine the critical timescales, and to source the data needed for model verification (which may be held by industry or managers). This stage can also be used to explain how to interpret uncertainty, probabilistic forecasts and lead-times, and to discuss realistic expectations about forecast skill. These issues are also revisited in the final implementation stage, but early discussion is important to enhance forecast acceptance. While remote communication via email is possible, site visits are critical to building understanding for both scientists and end users, and provides a solid foundation for forecast development.

In the second stage, the model performance is tested and evaluated (Fig. 5). Spatial and temporal forecast skill varies around Australia, depending on the particular environmental variable. Thus, forecast skill must be assessed for each application, even if the same environmental variable is being used. When the forecast product involves predicting not only

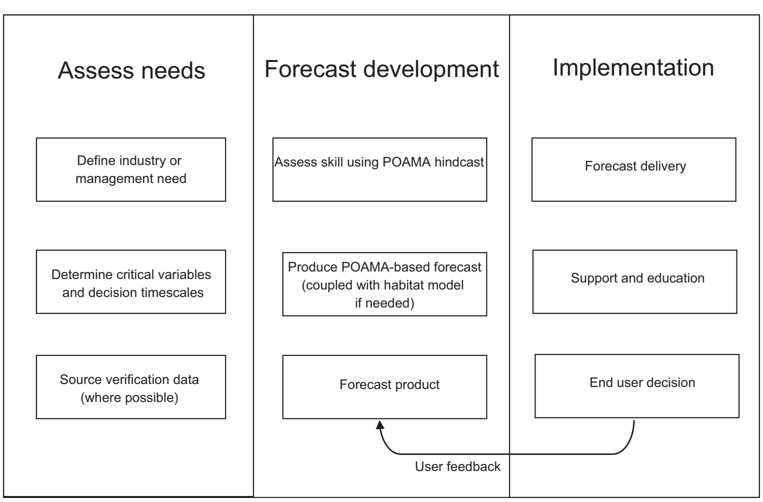


Figure 5. Stages in the development of a forecasting application and the important elements in each stage. After implementation there will need to be updates of the forecast skill, particularly if conditions are changing owing to climate change. POAMA, Predictive Ocean Atmosphere Model for Australia.

environmental variables, but also species distribution based on those environmental conditions (i.e. habitat forecasts), the skill of the habitat model must also be evaluated. In this case, historical biological data can be used to assess whether animals were found in places with environmental conditions they prefer according to the habitat model. Unlike climate-scale projections of biological response which are typically unverified (Brander *et al.*, 2013), seasonal forecasting allows comprehensive estimates of projection uncertainty, and thus can build user confidence in the tools. If the skill is considered high enough to be useful, forecasts products are then generated. Development of the forecast product, the appearance, user-friendliness and delivery mechanism, also benefit from stakeholder involvement. We have found that presenting a suitable range of options helps tune the final product delivered to end users (Fig. 4).

The third phase, implementation, involves operational delivery of forecasts, support and education around forecast interpretation, and gathering information about end-user decisions that can refine the particular product (Fig. 5). Forecasts have been delivered via public or password-protected websites, or emailed directly to users. With small user groups, email allows feedback and a greater personal engagement with the users; however, web-based delivery is more sustainable in the long-term as it can be almost fully automated, and ultimately managed by end users (provided the data processing continues). This sustainability is important as science research support tends to decline after a project to develop a forecast system ends. Support and education is critical, as evidence shows that several years are needed for some users to begin to make decisions based on forecasts, and levels of interest vary between users (Marshall *et al.*, 2011). Industry champions can enhance forecast uptake and dissemination, and if these can be identified in the first phase, forecast uptake is likely to be enhanced. Similar lessons emerge from development of agricultural forecast systems (Marshall *et al.*, 2011). These forecasts are being generated in response to industry needs, with both industry and government funding, and while we are establishing enduring delivery mechanisms, such as automated websites, long-term continuation is not guaranteed. In particular, ongoing extension work and validation will need dedicated funding.

Keeping track of end-user decisions (Fig. 5) is more difficult, however, as these are often commercial and hence confidential. However, trust between end users and the science research team can provide informal feedback. For example, some prawn farmers delayed stocking in response to projections for a cold period in 2011, and realized financial benefit as a result of savings in feed costs. This information can be useful in tuning forecast products, based on the types of decisions that are considered. In the case of fisheries management based on short-term habitat 'nowcasts', decisions were publicly reported and the use of the nowcasts increased over time (Hobday *et al.*, 2010). Similar approaches could be taken with seasonal forecasts, provided the management responses can be tracked. In the case of Tasmanian salmon farmers, during the period that forecasts have been delivered, some farm operators have changed from occasional implementation of response options to forecasts (e.g., increasing oxygenation of cages in warm waters) to permanent implementation of the action. This represents a risk management response, and while now forecast independent, illustrates a change in behavior as a result of a climate risk identified by the forecasts. In most cases, the seasonal forecast information will be only one of several factors behind a particular decision. Prawn farmers have market drivers that dictate when stocking of ponds or harvest must occur, and seasonal forecasts may only partially influence behaviors. Similarly, in the case of fishery managers in eastern Australia, spatial habitat forecasts are just one tool; quota availability, vessel monitoring, observers and fisher–manager relationships all contribute to the overall management decision taken (Hobday *et al.*, 2009). Thus, tracking direct responses to forecasts as a measure of forecast success is complicated.

The economic value of forecasting is even more difficult to quantify. Benefits must be assessed over a considerable period of time (say 10–20 years), as forecasts are probabilistic (they will be wrong in some years), and may only provide value in certain years (e.g., when particular environmental conditions are exceeded). In general, we argue that benefits will accrue though the use of forecasts, but to date we lack quantitative evidence for financial benefit for our case studies.

The use of seasonal forecasting to support seafood production can be extended to many other locations. National and global seasonal forecasts are issued for a range of large-scale drivers, such as ENSO (e.g., Hendon *et al.*, 2009), and the expected frequency of extreme weather events, such as cyclones (e.g., Werner and Holbrook, 2011). Seafood businesses and managers may already use these coarse forecasts; tailored local-scale forecasts can be considered complementary to these existing products. The POAMA seasonal forecasting model used in the examples presented here is global; similar models have been developed in other countries, although their application to fisheries is less advanced (http://www.washington.edu/news/2013/08/30/new-ocean-forecast-could-help-predict-fish-habitat-six-months-in-advance/). We have provided examples where the model forecasts had sufficient skill to be useful for decision support. In cases where even longer lead-times are required, or where model skill is lower, a range of options to improve the skill may exist, including forecast calibration and hybrid models combining statistical and dynamical forecasts.

Development of seasonal forecasting for the distribution of other marine species, such as turtles and seabirds, could be extended from existing efforts that describe environmental relationships (e.g., Howell *et al.*, 2008; Hazen *et al.*, 2013). These forecasts could then be used to minimize interactions with wild fisheries, as a component of dynamic spatial management (Hobday *et al.*, 2014). However, for such forecasts to be useful, there must be conservation management or fisher decisions that are made at lead-times that match the skill of the seasonal forecast (Fig. 1). One example might be in the designation of closed areas that are projected to contain the species of interest.

Use of seasonal forecasting can be considered to represent a risk-based approach to seafood production and management (Hobday *et al.*, 2008). Better managed marine resources are also likely to have improved resilience under climate variability and climate change (Marshall *et al.*, 2013). At longer timescales, climate change will also be a new factor for a range of businesses, and risk-based approaches are likely to be appropriate (Hobday and Poloczanska, 2010). It is unlikely that experience in managing for climate variability will be sufficient, as climate projections suggest that some environmental variables will move outside the envelope of previous experience. Given that climate variability has always had an influence on seafood production, and climate change has already begun to impact fisheries and aquaculture (Merino *et al.*, 2012; Pinsky and Fogarty, 2012), managers and operators in the seafood sectors that can manage proactively using seasonal forecasts will be in a better position to respond to the challenges of climate.

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