FISHERIES OCEANOGRAPHY

FISHERIES OCEANOGRAPHY Fish. Oceanogr. 25:1, 15–27, 2016

Cloudy with a chance of sardines: forecasting sardine distributions using regional climate models

ISAAC C. KAPLAN,[1]* GREGORY D. WILLIAMS,[1] NICHOLAS A. BOND,[2,3] ALBERT J. HERMANN[2,3] AND SAMANTHA A. SIEDLECKI[3]

[1]*Conservation Biology Division,NOAA Northwest Fisheries Science Center, 2725 Montlake Blvd E., Seattle, WA 98112, U.S.A.*

[2]*NOAA Pacific Marine Environmental Laboratory, 7600 Sand Point Way NE, Seattle, WA 98115, U.S.A.*

[3]*Joint Institute for the Study of the Atmosphere and Ocean, University of Washington, 3737 Brooklyn Ave NE, Seattle, WA 98105, U.S.A.*

ABSTRACT

Despite the significant advances in making monthly or seasonal forecasts of weather, ocean hypoxia, harmful algal blooms and marine pathogens, few such forecasting efforts have extended to the ecology of upper trophic level marine species. Here, we test our ability to use short-term (up to 9 months) predictions of ocean conditions to create a novel forecast of the spatial distribution of Pacific sardine, *Sardinops sagax*. Predictions of ocean conditions are derived using the output from the Climate Forecast System (CFS) model downscaled through the Regional Ocean Modeling System (ROMS). Using generalized additive models (GAMs), we estimated significant relationships between sardine presence in a test year (2009) and salinity and temperature. The model, fitted to 2009 data, had a moderate skill [area under the curve (AUC) = 0.67] in predicting 2009 sardine distributions, 5–8 months in advance. Preliminary tests indicate that the model also had the skill to predict sardine presence in August 2013 (AUC = 0.85) and August 2014 (AUC = 0.96), 4–5 months in advance. The approach could be used to provide fishery managers with an early warning of distributional shifts of this species, which migrates from the U.S.–Mexico border to as far north as British Columbia, Canada, in summers with warm water and other favorable ocean conditions. We expect seasonal and monthly forecasts of ocean conditions to be broadly useful for predicting spatial distributions of other pelagic and midwater species.

Key words: climate forecast system, ecological forecasting, Pacific sardine, regional ocean modeling system, *Sardinops sagax*

**Correspondence*. e-mail: Isaac.Kaplan@noaa.gov

Received 12 September 2014

Revised version accepted 9 October 2015

INTRODUCTION

The evolving science of ecological forecasting has emerged as an imperative to anticipate environmental change for human society (Clark *et al.*, 2001). Ecological forecasts help decision-makers and managers plan for the future, make informed decisions regarding alternative management choices and take appropriate actions to better manage natural resources. Consequently, ecological forecasting is considered one of the key science capabilities required to support U.S. coastal ecosystems into the future (Brandt *et al.*, 2006; Murawski and Matlock, 2006). Short-term forecasts of physics, on the scale of days to seasons, are familiar – we are accustomed to forecasts of tomorrow's weather or the outlook for the next hurricane season. However, to date, in marine systems ecological forecasts at this time scale have been primarily focused on the prediction of algal blooms, hypoxia and pathogens (Greene *et al.*, 2009; Stumpf *et al.*, 2009; Ali, 2011). Despite the significant groundwork in forecasting provided by these applications and by weather and climate science, few such forecasting efforts have extended to the ecology of upper trophic level marine species.

One forecasting tool that operates at this seasonal time scale and at the interface of physics and ecology is J-SCOPE: JISAO's Seasonal Coastal Ocean Prediction of the Ecosystem (http://www.nanoos.org/products/j-scope/home.php/). J-SCOPE has been developed for the northern California Current System along the west coast of North America to provide projections of physical, chemical and biological ocean properties on 6- to 9-month time horizons. The projections are testable and designed to be relevant to management decisions for fisheries, protected species and the ecosystem. These forecasts are derived using the output from the Climate Forecast System (CFS) model dynamically downscaled with the Regional Ocean Modeling System (ROMS). More detail on the J-SCOPE modeling system is provided below.

Pelagic species may be particularly responsive to seasonal and inter-annual variations in climate because they alter their distributions and migrations directly in response to ocean conditions (McGowan *et al.*, 2003; Brodeur *et al.*, 2005; Emmett *et al.*, 2005; Hooff and Peterson, 2006). For example, yearling salmon abundance has been correlated on an annual basis with water temperature, chlorophyll and copepod biomass in the northern California current (Peterson *et al.*, 2010; Yu *et al.*, 2012) and some of these parameters are used as indicators of early salmon survival that complement existing predictions of adult salmon runs (http://www.nwfsc.noaa.gov/research/divisions/fe/estuarine/oeip/index.cfm). Other highly mobile pelagic taxa, such as Humboldt squid (*Dosidicus gigas*) and jack mackerel (*Trachurus symmetricus*) may rapidly expand their range and become particularly abundant in new regions during years or seasons characterized by 'anomalous' sea surface conditions (e.g., salinity, temperature and dissolved oxygen)(Brodeur *et al.*, 2006; Chesney *et al.*, 2013).

The Pacific sardine (*Sardinops sagax*) is an ecologically important pelagic forage fish and fishery target in the California Current and is highly responsive to ocean conditions. The species migrates from southern California and Mexico in winter, to as far north as British Columbia during summer in years with warm water temperatures. Moreover, the 14–16°C regions of sea surface temperature (SST) where spring and summer spawning are commonly observed are highly variable in their spatial extent. A variety of studies have characterized its distribution and habitat associations in an effort to better assess abundance and optimize management (Logerwell and Smith, 2001; Emmett *et al.*, 2005; Kaltenberg *et al.*, 2010; Weber and McClatchie, 2010; Zwolinski *et al.*, 2011). Sardine spawning habitat, as measured by standardized egg surveys, has been associated with water masses having characteristic temperatures of 13.5–15°C and salinities <33.3 practical salinity units (Checkley *et al.*, 2000). Other environmental parameters, including primary productivity (Reiss *et al.*, 2008), upwelling rate (Lluch-Belda *et al.*, 1991), or zooplankton abundance (Lynn, 2003), have also been used to characterize sardine habitat. In Pacific Northwest waters, Emmett *et al.* (2005) showed that sardine density was related to salinity, temperature and chlorophyll-*a* levels, but at varying levels of significance depending on sardine size or life history stage. More recently, Zwolinski *et al.* (2011) developed a model to predict the habitat and seasonal migration pattern of sardines based on SST, chlorophyll-*a* concentration and the gradient of sea surface height.

Here, we test our ability to use short-term (up to 6–9 months) J-SCOPE predictions of ocean conditions to create a novel forecast of the spatial distribution of Pacific sardine. We use 2009 as a test year, estimating relationships between forecasted ocean conditions and sardine spatial distribution, and then quantifying the strength of these relationships. Models of sardine spatial distribution were fitted to three surveys available for 2009 from the U.S. Pacific Northwest and Vancouver Island, Canada. Finally, we provide a preliminary test of forecast skill, comparing predicted sardine spatial distributions for 2013 and 2014 to field observations.

METHODS

J-SCOPE oceanography model description

The J-SCOPE model system is based on the climate forcing as specified by the (CFS global climate model. The CFS is a coarse-scale, coupled atmosphere-ocean-land model that assimilates both *in situ* and satellite-based ocean and atmospheric data (Saha *et al.*, 2006, 2010). The CFS has been shown to forecast both PDO and ENSO indices up to 6 months in advance (Wen *et al.*, 2012).

We used CFS to force a high-resolution (grid spacing ~1.5 km) version of the ROMS (Shchepetkin and McWilliams, 2005) that includes a state-of-the-art biogeochemical module and nutrient, phytoplankton, zooplankton, detritus (NPZD) module (Banas *et al.*, 2009; Davis *et al.*, 2014) with an additional detrital pool and oxygen submodel (Siedlecki *et al.*, 2015). ROMS is configured for the Oregon, Washington and British Columbia (43–50°N) coast after Giddings *et al.* (2014). Our implementation of ROMS includes 17 rivers with daily discharge and temperature data from the USGS gage stations and an Environment Canada gauging station for the Fraser River as described by Giddings *et al.* (2014). The rivers enter the domain with constant saturated values of oxygen and a seasonal cycle for nutrients from a climatology (i.e., seasonal average) of USGS gage stations data described by Davis *et al.* (2014). For the forecasts, the rivers are forced using a seasonal pattern of local river discharge that is an average over 7 years (2000–2007). Western and southern boundary conditions on sea surface height, velocity, temperature and salinity are derived from the CFS, interpolated to the ROMS grid. Empirical relationships were derived relating nutrients and oxygen to salinity from the observations of Connolly *et al.* (2010) as described by Davis *et al.* (2014) and Siedlecki *et al.* (2015). The ROMS output features specific oceanic properties crucial to the nearshore and coastal marine ecosystems such as temperature, salinity, oxygen, chlorophyll and small zooplankton distributions, currents, and upwelling indices. Note that here for sardine we focus mainly on the J-SCOPE model system in the forecast mode, predicting 9 months forward from January 2009 and April 2013 and 2014, with no foresight about coarse scale (CFS) or fine scale (ROMS) ocean conditions for the year.

Oceanography model forecasts

The ROMS model, forced by CFS, predicts spatial patterns of temperature, salinity, nutrients, chlorophyll, zooplankton and oxygen for the coastal zone from Southern Oregon to the mid-west coast of Vancouver Island, British Columbia. Nine-month forecasts were produced for 2009 as well as for 2013 and 2014. The year 2009 was chosen as a test year it because it included typical summer winds (within 0.5 m s^{-1} of normal) and because of the availability of mooring observations for model validation. Additionally, we expected the moderate-to-weak El Niño conditions of 2009 to also occur during 2013, the first true forecast year for our exercise. (Only now do we know that El Niño that began to develop in fall 2012 failed to materialize in 2013.) Results are available on the Northwest Association of Networked Ocean Observing Systems (NANOOS) website (http://www.nanoos.org/products/j-scope/home.php/).

Oceanography model skill

In a separate manuscript summarized on the JSCOPE website, we consider the skill of J-SCOPE's predictions of ocean conditions. Here we summarize the model skill and performance to set the stage for sardine prediction, based on comparisons to a 2013 coast-wide cruise and satellite data. We use the JSCOPE ROMS in forecast mode, initialized in April 2013. We consider forecasts through October 2013 (i.e., projecting 1–6 months ahead).

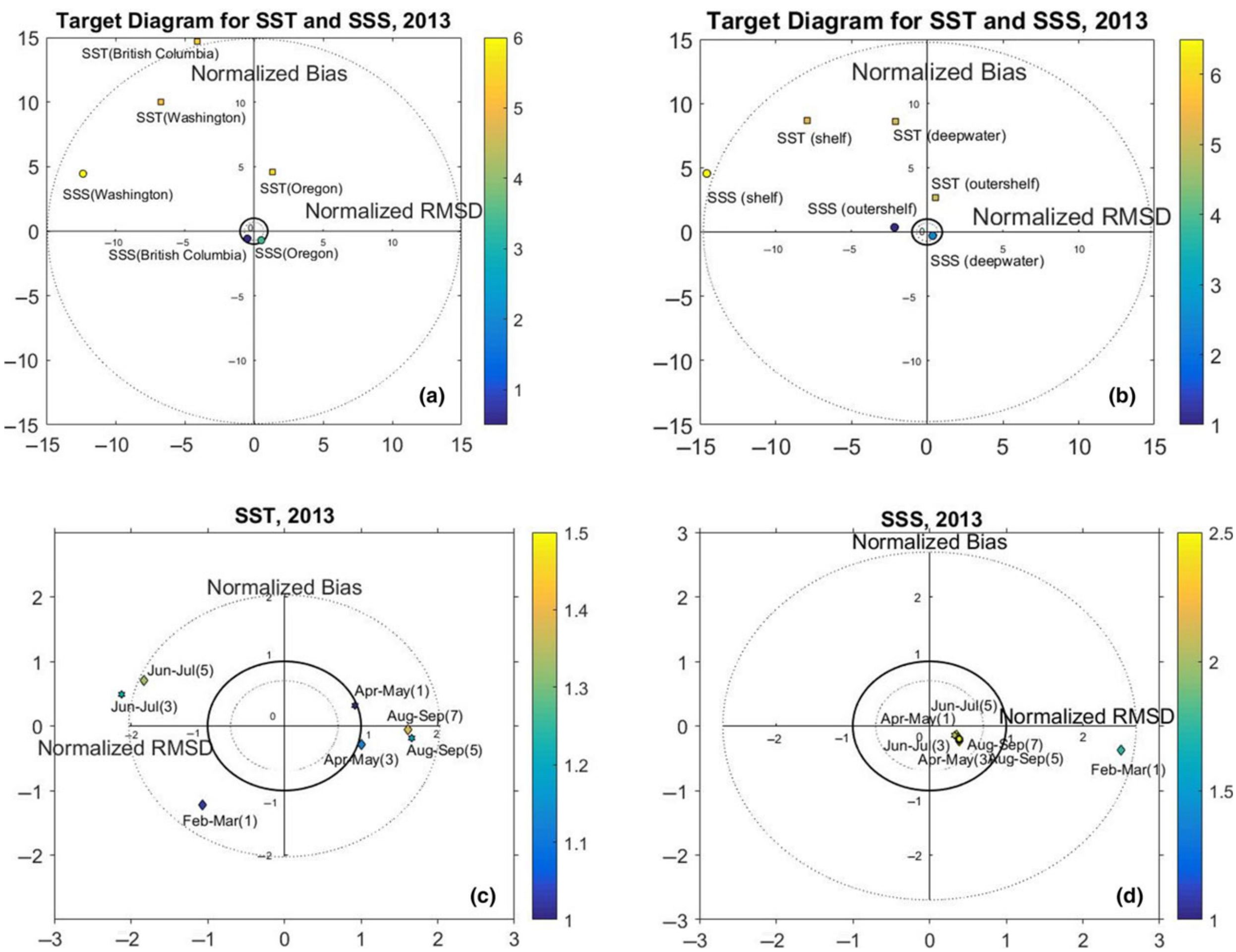
Model skill can be evaluated in the J-SCOPE forecasts; however, skill should also be understood in the context of the hindcast performance. In our case, a hindcast is an instance where data assimilation techniques in CFS (but not directly in ROMS) allow inclusion of hindsight knowledge about ocean conditions (e.g., from moorings or satellites) during the period of simulation. Below, in the context of the coast-wide cruise data, we discuss these two components of model skill: the comparison between observations and the hindcast, and the comparison of the hindcasts to the forecast used for sardine prediction.

Comparisons between the observations and modeled fields were made with target diagrams (Jolliff *et al.*, 2009), and provide a summary of the pattern statistics and model biases. In these diagrams, the distance from the origin is proportional to the total Root Mean Squared Difference (RMSD). Position on the x-axis informs whether the model's standard deviation is larger ($X > 0$) or smaller ($X < 0$) than the standard deviation of the reference field, in addition to providing information about the positive ($Y > 0$) or negative ($Y < 0$) bias. Modeled fields that fall within values of 1 of the RMSD and bias, each normalized by the normalized standard deviation, indicate a better than average modeling efficiency metric (MEF) (Stow *et al.*, 2009), and that the reference field and modeled points are positively correlated (Jolliff *et al.*, 2009).

To test model performance, the 2013 hindcast simulation was compared with co-located NOAA PMEL Carbon Cruise data (Feely *et al.*, 2015) (FigureS1). The model performs better with salinity and SST off the coast of Oregon and Washington than it does farther north (Fig. 1a). In addition, the model performs better in deeper water and on the outer shelf than it does near the coast (Fig. 1b). SST is generally biased high (Fig. 1a) although there is more skill on the outer shelf (Fig. 1b). In Washington, both salinity and SST have less variability in hindcasts than in observations (Fig. 1a). To test model predictability, the 2013 forecast was compared with the 2013 hindcast simulation. Results indicate that salinity is predicted with more skill than SST, showing minimal bias, and variability that is comparable to the variability in hindcasts and observations (Fig. 1b,d). SST has the most predictive skill in the spring (April to May, Fig. 1c) from both the January and April initialized forecasts.

We also compared J-SCOPE output to SST satellite data for 2013 to further assess the model's skill in simulating observed spatial distributions of SST, which is critical to predicting spatial habitats. Satellite data were monthly composite SST data provided by NOAA's Coastwatch program, derived from the AVHRR instrument aboard NOAA's POES satellites. Data were accessed through ERDDAP (http://coastwatch.pfeg.noaa.gov/erddap/index.html). Given the SST bias evident in the comparisons to NOAA PMEL Carbon Cruise data, we applied the method described below that estimates the bias but focuses on whether the relatively warm (and cold) patches are in the correct spatial location.

Figure 1. Target diagram (Jolliff *et al.*, 2009) for modeled fields from 2013 from the NOAA PMEL Carbon Cruise data. The *y*-axis is bias normalized by the standard deviation of the observations, and the *x*-axis is the bias-corrected Root Mean Square Difference (RMSD) or, also normalized by the standard deviation of the observations (a) Model performance as indicated by the comparison between the hindcast and the observations over the upwelling season (April –October) for particular regions of the domain. Symbols indicate sea surface temperature (SST) and sea surface salinity (SSS). (b) Model performance as indicated by the comparison between the hindcast and the observations over the upwelling season (April –October) for particular depth bins within the domain. The next two panels (c)–(d) relate to model predictability as indicated by the comparison between the forecast initialized in January (diamonds) and April (stars) and the hindcast: (c) SST, (d) SSS. The color indicates the RMSD.



We quantified model versus satellite similarity using the numerical fuzzy kappa method, which compares values (cell by cell) on two maps. A kappa statistic value of 100% is ideal. The method requires that the model (J-SCOPE) and data (satellite SST) are interpolated onto the same grid. For the purposes here, we use the 0.0125-degree grid from the satellite data, meaning approximately a 1.4-km grid spacing. The fuzzy kappa statistic allows consideration of a neighborhood of points, rather than a strict point-to-point comparison; it was recently suggested for use in oceanographic models by Rose *et al.* (2009) and we apply an implementation by Visser and De Nijs (2006). Based on correlation distances for the coastal ocean (Goebel *et al.*, 2014), we consider a 'neighborhood' of 5.6 km (four grid steps) with an exponential decline with distance. This means that the similarity calculation give some weight (50%) to cells 1 step away, and about 6% weight to cells 4 steps away. Cells greater than four steps away do not factor into the fuzzy kappa statistic. Importantly, we acknowledge that there is bias (temperature offset) in J-SCOPE. For each month, we calculated this bias (mean SST_{model} – mean SST_{data}), and use the bias-corrected spatial field to produce maps and for calculation of similarity statistics. In simple terms, the spatial comparison asks whether patches of warm and cool water are found in a similar location on the two maps although warm patches in J-SCOPE were typically degrees hotter than in the satellite data.

The results suggest that the model has substantial skill to capture spatial patterns of SST for the year 2013, up to 5 months in the future. The fuzzy kappa statistic was ~95% for months 1–5, then fell to 88% in month 6 (Figures S2–S5). In this sixth month (October), J-SCOPE predicted cold nearshore water, particularly south of the Columbia River, which was not observed in the satellite data (Figure S5). The bias correction was crucial; JSCOPE had mean values of SST 1–3 degrees warmer than data (satellite SST) for these months.

For the application of these forecasts to sardine distributions, three key points arise from the model skill tests above. First, there is a substantial bias in SST (J-SCOPE warmer than observations), and this is evident even in both forecasts and hindcasts. The SST bias means that the model is able to forecast the approximate location of relatively warm patches of water, no more than 6 months in advance, although absolute SST is less certain. The implication of this is that SST bias must be accounted for in the sardine modeling; below, to address this we intentionally fit sardine models to 2009 JSCOPE forecasts (not observations), so that parameter estimates applied to make 2013–2014 forecast predictions account for these warmer than observed temperatures. Second, model skill for SST is worst (most positively biased) in the north, and so we must carefully evaluate sardine distribution predictions for that region. Finally, the model (particularly when hindcasts are compared to observations) shows instances of lower variability than in observations, suggesting that some types of variability on fine spatial or temporal scales are not represented by J-SCOPE. We, therefore, expect a higher skill at predicting monthly, as opposed to daily statistics of the regional ocean. Therefore, the aim of the work below is to predict sardine distributions from monthly predictions of ocean condition, rather than daily scales.

Sardine data

We developed a generalized additive model (GAM) that predicts distributions of Pacific sardine in the northern California Current in 2009. We improve the power and geographic scope of our analysis by combining three 2009 sardine survey datasets, two from the USA and one from Canada. Although the sampling methodologies differ between surveys, described below, all are expected to reliably detect presence/absence within surveyed areas.

Northwest sardine survey (NWSS)

The Northwest Sardine Survey is an aerial survey developed by a consortium formed by the West Coast sardine industry (Jagielo *et al.*, 2011). The survey began with a preliminary study in 2008, with a full survey the following year. Surveys consist of aerial transects flown by spotter pilots, to identify sardine schools and estimate school surface area. We restrict our analysis to only presence/absence. In the Northwest Sardine Survey, sardine were identified via aerial photogrammetry, which in 2009 involved the use of 3660 individual photographs taken on August 19, 22, 23 and 24 (one additional day's sampling occurred south of the JSCOPE domain). Sampling extends along the entire coasts of Oregon and Washington with each transect extending from three nautical miles from shore westward to 35 nautical miles from shore.

The NWSS photographs are taken in rapid succession by spotter planes and may overlap (Jagielo *et al.*, 2011), leading to challenges with spatial autocorrelation and potentially over-emphasizing the effective sample size of this survey. Variograms suggest that spatial autocorrelation in sardine abundance declines at a minimum of approximately 1 km distance. However, this 1 km is finer than the resolution of the J-SCOPE ROMS, and furthermore aggregating NWSS data to this level would still result in NWSS contributing over 85% of the total sample size from the three surveys. To address both the spatial autocorrelation and sample size, along each NWSS transect, we aggregated points within each 0.1° of longitude (~7.5 km), which is an interval with minimal spatial autocorrelation. This results in 169 binned observations from the NWSS, comprising 48% of total observations from the three surveys.

West Coast Vancouver Island (WCVI) trawl survey

The West Coast of Vancouver Island sardine and pelagic ecosystem night time trawl survey in 2009 involved net sampling, with the net opening 12 m high, 32 m wide, and with a towing speed of approximately 2.5 m s^{-1} (Flostrand *et al.*, 2012). Sampling was conducted with a model 250/350/14 mid-water rope trawl. In 2009, the headrope of the tow was consistently near the surface (<4-m deep), as intended to capture sardine expected to be in the upper water column at night. Sampling in 2009 spanned the 15-day period from 22 July to 5 August. Sampling extended from north of 50°N latitude to the southern end of Vancouver Island (48.4°N latitude), but we use only presence/absence data from the 96 sets south of the northern boundary of the ROMS model (50°N). Sampling followed line transects with *ad hoc* spatial patterns.

NOAA predator survey

The Predator Survey (Emmett *et al.*, 2001, 2005), begun in 1998, involves a series of surface trawl sets conducted at night along two transects at the mouth of the Columbia River. A Nordic 264 rope trawl measuring approximately 12-m deep by 28-m wide is deployed using towing speeds of approximately 1.5 m s^{-1}. In 2009, 84 stations were sampled over 24 sampling days, spanning from 9 May to 25 August. Sardines were absent prior to 24 May. Sardine density per trawl was recorded, but here we focus on the presence/absence only.

Ocean conditions extracted from J-SCOPE forecasts

The ROMS model used in the J-SCOPE forecast predicts time-varying, three-dimensional fields for a broad set of physical and biological variables. Here we focus only on variables likely to be important to sardines, measured either at the surface or integrated over the top 10 m. Net sampling from the three surveys either focused on the top 10 to 12 m (Predator survey, WCVI survey) or reported that the bulk of fish occurred at those depths (NWSS). From ROMS, we extracted salinity (averaged over top 10 m), chlorophyll-*a* in surface waters (top 2 m) and SST. Chlorophyll-*a* was averaged over the top 2 m to be consistent with the depth of satellite detection, and the temperature was extracted at the surface to maintain comparability with satellite observations used in prior studies (Checkley *et al.*, 2000; Reiss *et al.*, 2008; Zwolinski *et al.*, 2011).

From the sardine surveys, we record presence or absence per location, latitude and longitude. For each survey point and date, we identified the nearest point on the ROMS grid and assigned predicted ocean conditions from the grid point to the survey point on that date.

Statistical analysis

We used GAMs to predict sardine presence or absence under forecasted conditions (monthly averages). GAMs capture the relationship between predictors (ocean condition) and response (sardine presence or absence) without pre-specifying the form of such relationships. We used a binomial error distribution and a logit-link function [mgcv package in *R*, Wood (2004)], according to Zwolinski *et al.* (2011). We initially explored GAMs allowing interactions between paired combinations of temperature, salinity and chlorophyll-*a*, but then limited the model to include only the most important interaction, between salinity and temperature, as well as a smoothed term for chlorophyll alone. We applied smoothers with a maximum-basis dimension of 3; allowing additional smoothing (higher dimensions) led to multi-modal response curves that are unlikely to be realistic based on previous sardine studies. We used the 'select' option in the *gam* function within mgcv to handle model selection; the result was that chlorophyll was effectively eliminated from the model (Wood, 2006), leaving a final model of *sardinePresence ~ te(temperature, salinity, k = 3)*. We report standard measures of model fit including R^2, percent of deviance explained and generalized cross-validation scores (GCV). The predictive and explanatory area under the curve (AUC), described in more detail below, were also calculated for 2009 to assess model fit, and to test skill for 2013 and 2014. AUC calculations follow the methods of Zwolinski *et al.* (2011).

AUC is a model selection criterion that tests the ability of a model to discriminate between presence and absence (Fielding and Bell, 1997). Developed by radar operators during World War II, it tests the ability of a model (or radar operator) to discriminate true (real world) presences and absences of sardines (or ships). Specifically, it plots model skill in terms of two axes: (i) model sensitivity, the proportion of true presences that the model predicts as true; and (ii) the false positive rate, the proportion of true absences that the model predicts as present. AUC values of 0.5 suggest a model that performs no better than random, and AUC values of 1 are ideal. AUC is perhaps the most straightforward way to assess model skill, and we evaluate two types: predictive and explanatory AUC. For the year 2009, we calculated predictive AUC by randomly selecting 80% of points as a learning set to fit the GAM, then testing model skill against the remaining 20% of observations. Explanatory AUC for 2009 examines each of the three datasets (NWSS, WCVI and Predator surveys) individually, testing the model skill of the final fitted model to predict observations within each survey.

As a preliminary test of forecasting skill, we also calculated AUC for 2013 and 2014, true forecast years for which limited data are available. Predictions for 2013 and 2014 were based on the GAM model fitted to 2009 data. From the August WCVI survey, we obtained 51 additional tows for 2013 and 59 additional tows for 2014, in which no sardine were detected. Additionally, midwater trawl data from July and August 2013 and 2014 are available from the NOAA Southwest Fisheries Science Center Coastal Pelagic Species Life History Program (ERDDAP 2015). For our model domain, sardine presence was recorded in two of 11 of these survey points in July 2013, 14 of 44 survey points in August 2013, two of 28 survey points in July 2014 and five of 21 points in August 2014. Combining the WCVI and NOAA Coastal Pelagic Species Life History Program data, we view August 2013 and 2014 as having a minimal sample size to quantitatively test forecast skill.

For the final GAM, we inspected plots of residuals and effects of each smoothed term, holding all other predictors at average levels. We also plotted maps of observed and predicted presence and absence to assess model skill in different geographic regions of the three surveys available for 2009, and the two surveys available for 2013 and 2014.

RESULTS

The J-SCOPE predictions of ocean condition contain sufficient information to forecast sardine presence/absence 5–8 months in advance. The GAM model has moderate (not excellent) predictive power, but the ability to produce forecasts is novel and has not been possible with previous approaches relating sardine distribution to the ocean environment.

The fitted GAM model estimated significant relationships between sardine presence and 2009 forecasts of temperature and salinity. GCV was 1.20, R^2 was 0.065 and 6.8% of the deviance was explained. Predictive AUC for 2009 was 0.67 ± 0.09, suggesting the model could predict the presence of sardines at sampled locations and sampled dates in 2009 with moderate skill. Specifically, a predictive AUC value of 0.67 implies that 67% of the time, a survey point where fish were actually observed will have a predicted probability of presence greater than a randomly selected survey point where sardine were absent. The explanatory AUC for 2009 was highest for the NOAA Predator Survey (0.75), and lower for the NWSS dataset (0.67) whereas explanatory AUC for the 2009 WCVI survey was poor (0.33).

Diagnostic plots were used to visualize and further characterize parameter relationships in the GAM. Plots revealed that the predicted relationships between sardine presence and ocean conditions were generally consistent with other published literature (Fig. 2) (Checkley *et al.*, 2000; Emmett *et al.*, 2005; Zwolinski *et al.*, 2011). Sardine presence was more likely to occur at lower salinities and warmer temperatures, with a slight decline in sardine at temperatures >16° C (Fig. 2). There is a strong interaction between salinity and temperature (Fig. 3), with salinities >30 parts per thousand reducing the probability of sardine presence even when temperature was optimal.

Maps of sardine survey points superimposed over model predictions of sardine presence at these same points provided a rapid approach to validate and visually assess the geographic extent and spatial accuracy of these predictions. The model correctly predicted suitable habitat (surface ocean conditions) in 2009 for sardine in a variety of coastal areas near the Columbia River, Grays Harbor and Willapa Bay coastal estuaries (U.S.), and off the northwestern and southwestern coastline of Vancouver Island, BC (Canada) (Fig. 4). The model also correctly predicted large areas of unsuitable habitat along much of the Oregon coast. In other areas, such as off central Vancouver Island (~126° west longitude), the model predicted sardine presence although sardine were not observed in the WCVI survey.

The model forecast that in August of 2013 the areas with the highest probability of sardine presence (or suitable habitat) would be off the Columbia River and the Washington Coast, extending no farther north than the southern coast of Vancouver Island (Fig. 5). The J-SCOPE CFS-ROMS projections underlying this

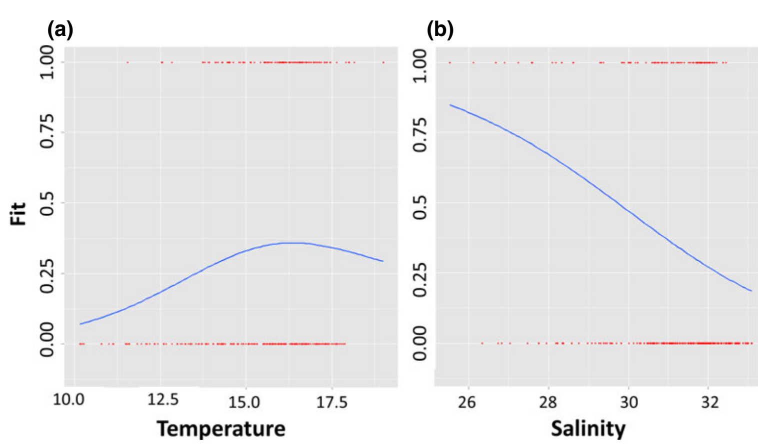


Figure 2. Generalized addictive model (GAM) plots for temperature and salinity. The *y*-axis is probability of sardine presence, for a given value of the variable represented on the *x*-axis. In each plot, the other variable is held at its mean value. Red points are observed presence (*y*-value of 1) and absence (*y*-value of 0).

Figure 3. Contour plots displaying the predicted probability of sardine presence versus temperature and salinity. Blue areas indicate lowest probability of sardine presence and yellow represents probabilities >0.6.

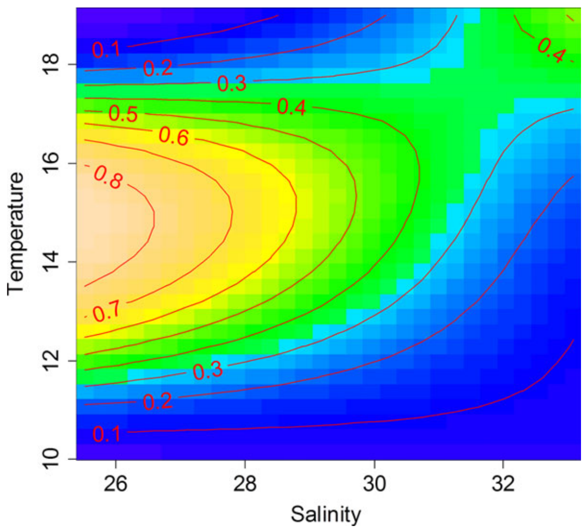
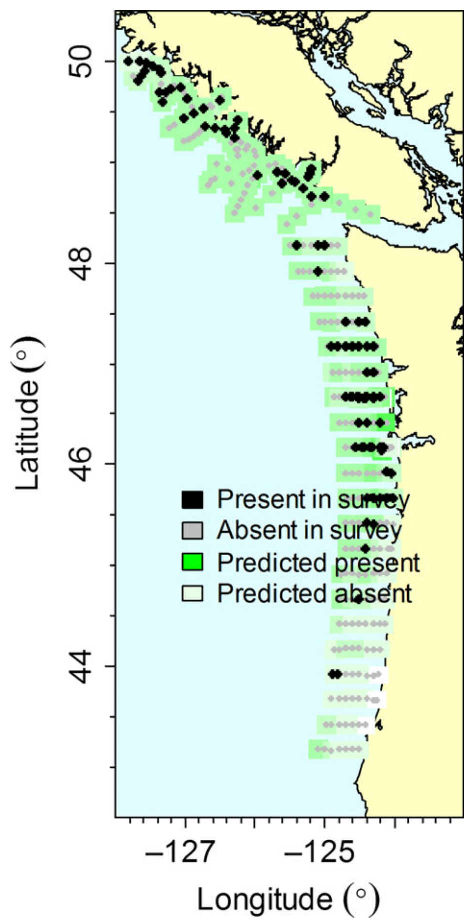


Figure 4. 2009 field survey locations (black and grey points) with the model prediction of probability of sardine presence for the same locations (represented as a continuous gradient from 0, white, to 1, green).



were based on forecasts initialized to represent 1 April, 2013, and hence were forecast 5 months in advance. Field observations support the presence of sardine off the Columbia River and Washington State, but the August WCVI survey did not detect any sardine off southern Vancouver Island (Fig. 5). Thus, the model captures the observations off Washington and Oregon but over-predicts sardine presence off a portion of Vancouver Island. The AUC for August 2013 is 0.85, beating the null expectation of 0.5.

For July 2013, sample sizes are much smaller, but model performance appears to be similar to that for August. The model forecasts sardine presence (or suitable habitat) off the Columbia River and the Washington Coast, but also off the southern coast of Vancouver Island (Figure S6). The 11 observations from the SWFSC Coastal Pelagic Species Life History Program suggest that sardine were present in southern Oregon (FigureS6), and fishery records indicate that 24 000 metric tons were landed at Columbia River ports and farther north in Washington (PACFIN, 2015). There were no fishery landings in British Columbia in 2013 (Hill *et al.*, 2015), reinforcing the pattern that the model captures Oregon and Washington observations but over-predicts sardine presence for the southern portion of Vancouver Island. AUC is 1.0 but is based on only two records of sardine in the 11 observations.

The model forecast that in August 2014 the areas with the highest probability of sardine presence (or suitable habitat) would be off the Washington and Oregon Coast, with a poor habitat off Vancouver Island (Fig. 6). In concurrence with this, the August WCVI survey did not detect any sardine off Vancouver Island, whereas the SWFSC Coastal Pelagic Species Life History Program survey detected sardine off the Columbia River and Oregon. The J-SCOPE projections underlying this were initialized to represent 1 Apri, 2014 (a lead time of over 4 months), yet AUC for August 2014 was 0.96.

Forecasts for July 2014 were similar to August, with areas of highest probability for sardine predominately off Oregon and Washington (Figure S7). AUC was 0.5 but based on a very small sample size (two records of sardine among 28 observations). Qualitatively, taken together the July and August 2014 predictions suggest that J-SCOPE correctly forecast that sardine would be found off Oregon and Washington, but would fail to

Figure 5. Predicted August 2013 probability of sardine presence over the J-SCOPE model domain, overlaid with field observations from the WCVI survey and the SWFSC Coastal Pelagic Species Life History Program.

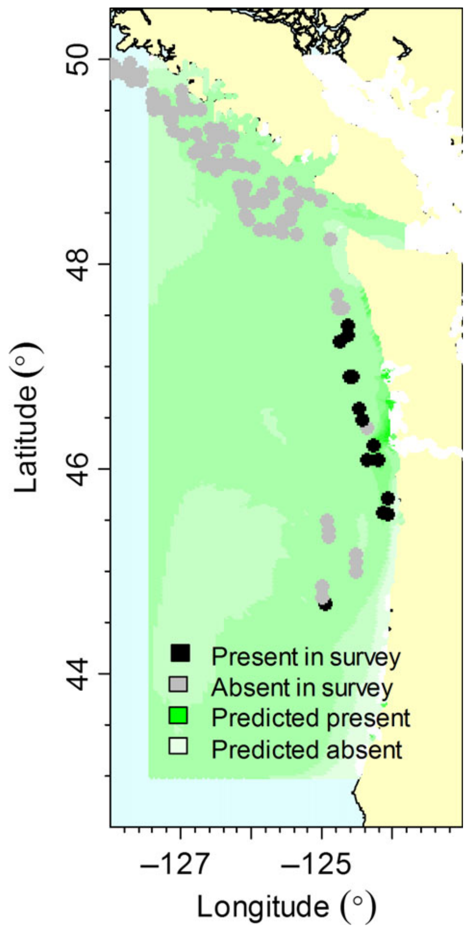
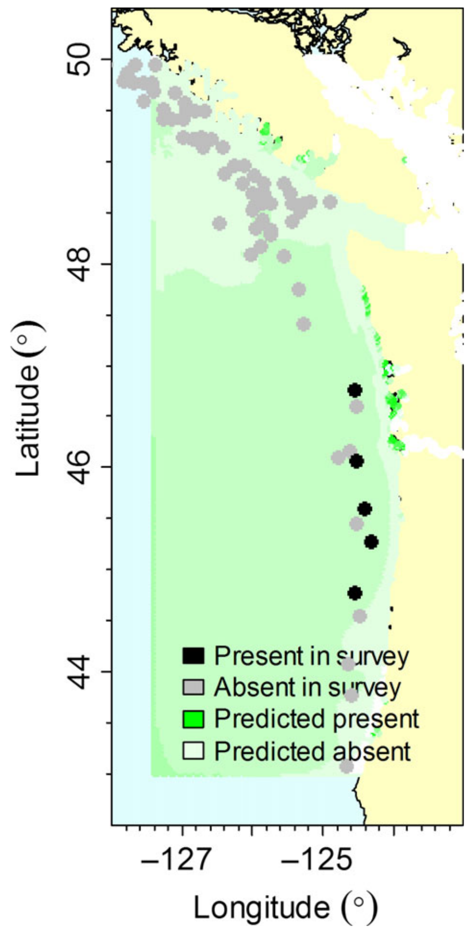


Figure 6. Predicted August 2014 probability of sardine presence over the J-SCOPE model domain, overlaid with field observations from the WCVI survey and the SWFSC Coastal Pelagic Species Life History Program.



reach British Columbia. In agreement with this, there were no sardine fishery landings in British Columbia at any point during 2014, but 16 000 metric tons landed in Oregon and Washington (Hill *et al.*, 2015).

DISCUSSION

The key innovation we provide here is the ability to forecast, with moderate skill, sardine distributions 4–8 months in advance. Our research suggests that relatively simple models using predictions of temperature and salinity from the J-SCOPE system can be used to forecast the distribution of sardines.

Pacific sardine are an abundant coastal pelagic species, with high ecological and economic relevance that is complicated by their migrations and distributional shifts between the U.S., Canada and Mexico. The total abundance of the northern subpopulation had a recent peak abundance of over 1 million metric tons in 2006–2007, then declined to less than 100 000 metric tons in 2015 (Hill *et al.*, 2015). Prior to this decline, sardine were consistently one of the top two finfish species by U.S. landings. In addition to being a key fishery species, sardine and other small pelagic fish are considered an important trophic link in the California Current, particularly for predators such as seabirds, salmon, tunas and some rockfish (Dufault *et al.*, 2009). Ecosystem models of this system (Kaplan *et al.*, 2013) and others (Smith *et al.*, 2011; Pikitch *et al.*, 2012) underscore the role of these species in marine ecosystems. Based on the ecological and economic roles of sardines and anchovies, as well as time series of field observations, these species are key indicators that are tracked and reported to managers as part of the California Current Integrated Ecosystem Assessment (Levin *et al.*, 2013). In the Integrated

Ecosystem Assessment, the emphasis is not just on total abundance trends, but regional differences driven by local ocean conditions such as those modeled here.

Potential role of forecasts for sardine and other pelagic species

Our method could serve as an early warning signal for fishery managers who make decisions on a monthly or quarterly basis, for instance to adjust harvest or to change areas open to fleets, despite the strong response of the components to climate and physical forcing (Bjorkstedt, 2010; Keller *et al.*, 2010; Keister *et al.*, 2011). For sardine specifically, the stock is shared jointly between the U.S., Canada and Mexico, with the U.S. assigned a fixed fraction (87%) of a tri-national harvest guideline. However, the seasonal migration of sardine from southern California to the northern regions is highly variable, with the stock failing to reach Canada in certain years (such as 2013 and 2014). Our aim here is to provide a warning that such distributional shifts may be impending. Given the assumptions and simplifications in the oceanographic model as well as the sardine GAMs, we do not foresee the method here as one to predict exact fish school location; the goal is to forecast monthly averages that suggest the approximate extent of sardine distribution. The forecasts here are 4- to 8-month projections (from starting dates of January 2009 and April 2013 and 2014), with good performance in the 4–5 month range, as observed for summer 2013 and 2014.

We expect forecasts of ocean conditions to be broadly useful for predicting spatial distributions of other pelagic and midwater species. For instance, Agostini *et al.* (2006) showed that Pacific whiting (*Merluccius productus*) follow poleward currents, whereas albacore tuna typically track SST (Alverson, 1961; Laurs *et al.*, 1984). Coho salmon survival (rather than spatial distribution) has been shown to be closely related to the dominance of boreal copepods in the California Current (Peterson, 2009); copepods abundance in turn appears related to water transport (Bi *et al.*, 2011; Keister *et al.*, 2011;). These aspects of ocean currents and temperatures are forecast by the CFS-ROMS system developed here, and the observed ecology of these species can similarly be tested against model predictions. The value of seasonal forecasts for fisheries management has been demonstrated for salmon fisheries in Alaska's Bristol Bay salmon fishery (Hyun *et al.*, 2005). Most promisingly, in Australia a predictive ocean-atmosphere model (Spillman and Alves, 2009) somewhat similar to J-SCOPE has been applied to predict distributions of tuna (Hobday *et al.*, 2011; Eveson *et al.*, 2015). These Australian case studies emphasize the prediction of specific phenomena that trigger stakeholder decisions (Hobday *et al.*, 2015), for instance, shifts in the northern extent of tuna habitat and, therefore, the probability of tuna catch, similar to our motivation for forecasting sardine migration.

Caveats and context

Other authors have provided similar, or even more detailed, relationships between ocean conditions and sardine distribution, although not in forecast mode. For instance, Emmett *et al.* (2005) found that small- and medium-sized sardines collected in surface trawls off the Pacific Northwest were more strongly positively related to temperature than were adults, whereas chlorophyll-*a* was an important explanatory variable for juvenile and adult stages but not for eggs or larvae. Our study did not differentiate between age-classes of sardine, a factor that may be used to refine future iterations of the model. Zwolinski *et al.* (2011) used SST, chlorophyll-*a* concentration and the gradient of sea surface height to predict potential sardine habitat throughout the California Current. Although their predictions were based on the presence of sardine eggs in southern and central California surveys, they validated their predictions for distributions of the northern stock with fishery landings and net sample data. Our work benefits from and further supports these previous efforts to define factors that drive sardine distributions. Finally, we note that our model does not link sardine distribution to stock size (MacCall, 1990), which may be important towing to the recent decline in abundance.

The work presented here can be improved by validation against additional years of data from the three sardine surveys, as well as additional net or acoustic surveys. Our aim was to continue the J-SCOPE modeling system to provide the oceanographic projections for this validation. Statistical relationships could be fine-tuned to differentiate between age-classes of sardine, or to predict abundance rather than simply distribution.

CONCLUSIONS

Pacific sardine are a flagship species for understanding the effects of oceanography, climate and climate change on fish species in the California Current. In addition to the temperature responses of sardine spatial distribution, the sardine stock–recruitment relationship has been shown to respond to temperature (Jacobson and MacCall, 1995; Lindegren and Checkley, 2012). Based on those studies, sardine is the only

U.S. West Coast species managed with a harvest control rule that varies as a function of temperature (Hill *et al.*, 2012). Rykaczewski and Checkley (2008) have proposed upwelling mechanisms that may underlie these statistical relationships with temperature. The behavior of the stocks under climate shifts such as El Niño and the Pacific Decadal Oscillation are also relatively well understood (Chavez *et al.*, 2003). In light of these drivers of recruitment and distribution, King *et al.* (2011) and Freon *et al.* [2009, in Checkley *et al.* (2009)] discuss how climate change may impact sardine populations. Our immediate goal of forecasting short-term responses of sardine to ocean conditions is more modest, but can inform longer-term projections of sardine response to a changing California Current.

ACKNOWLEDGEMENTS

Two anonymous reviewers provided insightful and constructive advice on an earlier version of this analysis. Ole Shelton, Jennifer Boldt and Jake Schweigert provided comments on the manuscript. Ole Shelton provided statistical advice, and Juan Zwolinski's R code was the starting point for the GAMs here. Data were provided by Linnea Flostrand, Jennifer Boldt and Jake Schweigert, Department of Fisheries and Oceans Canada; Tom Jagielo and Jerry Thon, Northwest Sardine Survey; Bob Emmett, NOAA NWFSC, and Sam McClatchie, Emmanis Dorval, and Juan Zwolinski, NOAA SWFSC. NOAA Carbon Cruise salinity and temperature data were provided by Simone Alin, PMEL. Thanks goes to Tam Nguyen who created Figure 1 to represent the model skill. Funding was provided by the NOAA Fisheries and the Environment (FATE) program and NOAA NWFSC.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

Figure S1. Sample locations for sea surface temperature and salinity from the NOAA PMEL Carbon Cruise in 2013.

Figure S2. Fuzzy kappa statistic (Visser and De Nijs, 2006; Rose *et al.*, 2009) measuring J-SCOPE model skill for sea surface temperature (SST), 1–6 month lead times. Kappa statistic of 1.0 is ideal. Average monthly fields compared to satellite monthly composite. Note each month's model predictions have been bias corrected by 1–3 °C to account for warmer average predictions in J-SCOPE relative to satellite observations.

Figure S3. Model skill for 2013, comparing satellite sea surface temperature (SST) monthly composite to J-SCOPE monthly mean (1 month ahead).

Figure S4. Model skill for 2013, comparing satellite sea surface temperature (SST) monthly composite to J-SCOPE monthly mean (3 months ahead)

Figure S5. Model skill for 2013, comparing satellite sea surface temperature (SST) monthly composite to J-SCOPE monthly mean (6 months ahead)

Figure S6. Predicted July 2013 probability of sardine presence over the J-SCOPE model domain, overlaid with field observations from the SWFSC Coastal Pelagic Species Life History Program.

Figure S7. Predicted July 2014 probability of sardine presence over the J-SCOPE model domain, overlaid with field observations from the SWFSC Coastal Pelagic Species Life History Program.