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Improved management of small pelagic fisheries through seasonal climate prediction

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Abstract. Populations of small pelagic fish are strongly influenced by climate. The inability of managers to anticipate environment-driven fluctuations in stock productivity or distribution can lead to overfishing and stock collapses, inflexible management regulations inducing shifts in the functional response to human predators, lost opportunities to harvest populations, bankruptcies in the fishing industry, and loss of resilience in the human food supply. Recent advances in dynamical global climate prediction systems allow for sea surface temperature (SST) anomaly predictions at a seasonal scale over many shelf ecosystems. Here we assess the utility of SST predictions at this "fishery relevant" scale to inform management, using Pacific sardine as a case study. The value of SST anomaly predictions to management was quantified under four harvest guidelines (HGs) differing in their level of integration of SST data and predictions. The HG that incorporated stock biomass forecasts informed by skillful SST predictions led to increases in stock biomass and yield, and reductions in the probability of yield and biomass falling below socioeconomic or ecologically acceptable levels. However, to mitigate the risk of collapse in the event of an erroneous forecast, it was important to combine such forecast-informed harvest controls with additional harvest restrictions at low biomass.

Key words: climate prediction; ecosystem-based management; fisheries management; forage fish; harvest guideline; Pacific sardine; seasonal forecast.

Introduction

It has long been recognized that fish populations fluctuate in response to climate variability (Lehodey et al. 2006, Ottersen et al. 2010), with some of the most notorious examples of climate effects on fisheries coming from small pelagic species (Soutar and Isaacs 1969, Baumgartner et al. 1992, Alheit and Hagen 1997, Field et al. 2009, Finney et al. 2010). When periods of climate-driven reduced productivity are not recognized, continued high fishing rates can have catastrophic consequences, exemplified by the Pacific sardine fishery demise in the 1950s (Murphy 1966, Essington et al. 2015), or the collapse of the Peruvian anchoveta fishery in the 1970s (Sharp 1987). Climate effects of fisheries are complex, and may also be positive, with abundance increasing in specific areas as a result of increasing productivity or distributional shifts (Hare et al. 2010). The inability to anticipate such increases in fish biomass can lead to lost income opportunities and unexpected economic consequences. For instance, unanticipated temperature-induced changes in the timing of Gulf of Maine Atlantic lobster life-cycle transitions resulted in an extended 2012 fishing season and record landings, but outstripped processing capacity and market demand, leading to a collapse in prices and an economic crisis in the lobster fishery (Mills et al. 2013).

Despite the importance of climate variability in driving fish population dynamics, and the potentially disastrous consequences of not incorporating information about climate-driven low productivity regimes (Murphy 1966, Sharp 1987, Essington et al. 2015, Pershing et al. 2015, Pinsky and Byler 2015), management targets are largely set without explicitly accounting for environmental variability (Skern-Mauritzen et al. 2016). One reason for this is that a full understanding of the linkages between climate and fish population dynamics is difficult to achieve, with many relationships breaking down over time (Myers 1998). Furthermore, strategic evaluations of alternative management strategies including environmental factors have reported mixed results in terms of improved management performance (Basson 1999, MacCall 2002, De Oliveira and Butterworth 2005, A'mar et al. 2009, Ianelli et al. 2011, Punt et al. 2013, Szuwalski and Punt 2013).

Recent advances in dynamical global climate forecast systems at the seasonal scale raise prospects for improved utility of these tools in developing new, forecast-informed, fisheries management strategies. SST forecasts at a spatial (i.e., coastal shelf) and temporal (i.e., monthly) scale

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relevant to the fisheries management decision process have shown high predictive skill for many continental shelf ecosystems (Stock et al. 2015). Such predictions already support more effective and proactive dynamic spatial management strategies of select marine resources (Hobday et al. 2011, 2014), and have been employed to improve efficiency and planning of the fishing and aquaculture industry (Spillman and Hobday 2014, Eveson et al. 2015, Spillman et al. 2015). It remains to be assessed if, given their uncertainty and the uncertainty of empirical environment–recruitment relationships, these forecasts can improve fisheries management performance by producing better stock biomass estimates on which to base catch target decisions.

Here we develop a proof of concept integration of seasonal climate forecasts into the fisheries management process using the Pacific sardine (*Sardinops sagax*) U.S. stock as a case study. The Pacific sardine fishery was first developed at the beginning of the 20th century, and by the 1940s it had become the largest in the Western hemisphere (Schwartzlose et al. 1999). However, it dramatically collapsed in the 1950s (Murphy 1966), likely due to a combination of overfishing and adverse environmental conditions (Zwolinski and Demer 2012, Lindegren et al. 2013, Essington et al. 2015), only recovering in the late 1990s (Zwolinski and Demer 2012). Such extreme biomass fluctuations were common even before the onset of fishing (Soutar and Isaacs 1969, Baumgartner et al. 1992, Field et al. 2009), and have exhibited a strong relationship with SST (Lindegren et al. 2013). Indeed, Pacific sardine is one of the few fisheries in the world whose current harvest control rule incorporates environmental information, SST during the three preceding years (Hill et al. 2010). The value of the integration of short-term SST predictions into the fisheries management framework was evaluated by comparing four control rules for setting harvest guidelines (HGs) differing in their level of integration of environmental and forecast information. These HGs are illustrated in Fig. 1 and are described fully in the Methods.

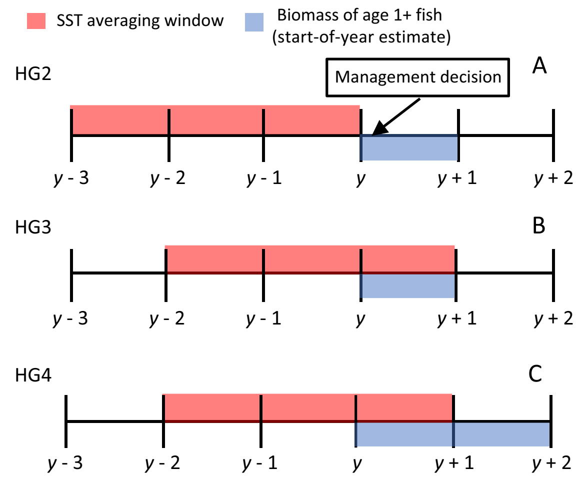

FIG. 1. Management decision timeframe relative to data inputs for the three alternative harvest guidelines (HGs). The three-year (year, y) sea surface temperature (SST) average influences the exploitation rate that would produce the maximum sustainable yield (E_{msy}) used in the HG.

METHODS

Sea surface temperature seasonal forecast

In the current stock assessment for Pacific sardine, the sardine–SST relationship depends on the mean annual 5–15 m depth temperature obtained from the California Cooperative Oceanic Fisheries Investigations (CalCOFI) survey (Hill et al. 2010). The robust relationship between sardine recruitment and SST (Jacobson and MacCall 1995, Myers 1998, Deyle et al. 2013, Jacobson and McClatchie 2013, Lindegren and Checkley 2013) may be a result of direct temperature effects on metabolism affecting larval growth and survival (Lluch-Belda et al. 1991), as well as changes in prey availability (Rykaczewski and Checkley 2008), predation mortality (Bakun and Broad 2003), and larval retention (Lluch-Belda et al. 1991, Nieto et al. 2014) of which SST is an indirect proxy. Here, we use monthly SST forecasts over the same CalCOFI survey area (Appendix S1: Fig. S1) using the NOAA Geophysical Fluid Dynamics Laboratory's (GFDL) CM 2.5 FLOR global climate forecast system, with coupled atmosphere, land, ocean, and sea ice components developed at the National Oceanic and Atmospheric Administration Geophysical Fluid Dynamics Laboratory (GFDL; Vecchi et al. 2014), which is part of the U.S. National Weather Service's operational North American Multi-Model Ensemble for seasonal prediction (NMME). Its atmospheric resolution is ~50 km, and its ocean resolution 1° (~100 km), increasing to 1/3° (~40 km) near the equator (Vecchi et al. 2014). This prediction system has shown SST prediction skill within the California Current LME (Stock et al. 2015). The seasonal SST forecasts are operational and made publicly available every month through the NMME website and GFDL (both *available online*).[8, 9] Retrospective forecasts going back to 1982 are available through both the NMME and GFDL data archives (both *available online*).[10,11]

Briefly, to compute a forecast, the atmosphere, land, ocean, and sea ice are initialized globally on the first day of the specified *initiation month.* Monthly climate forecasts up to a 12 *month lead* are then computed from this initial climate state. Ocean and sea ice initial conditions are obtained from GFDL's Ensemble Data Assimilation System (Zhang et al. 2007), while atmospheric and land conditions are estimated from a suite of SST forced atmosphere-land only simulations. For each forecast

[8] http://www.cpc.ncep.noaa.gov/products/NMME/
[9] http://www.gfdl.noaa.gov/cm2-5-and-flor
[10] https://www.earthsystemgrid.org/dataset/nmme.output.html
[11] http://nomads.gfdl.noaa.gov/dods-data/NMME/

run, 12 ensemble member forecasts are produced, each arising from slightly different but equally plausible initial conditions.

The procedures described in Stock et al. (2015) were used to assess prediction skill of the ensemble mean of these 12 forecasts. A total of 4032 (12 initiation months × 12 lead months × 28 yr) retrospective ensemble mean SST anomaly monthly forecasts from 1982 to 2009, were extracted from the GFDL model archive. Prediction skill was evaluated by computing an anomaly correlation coefficient (ACC) between the forecast and monthly averaged daily NOAA version 2 optimally interpolated daily high-resolution-blended SST anomalies (OISST, Reynolds et al. 2007) over the same CalCOFI survey area. The same 1982–2009 period was used to compute OISST anomalies. Finally, to determine the added value of the dynamical climate system, we compared the dynamic SST anomaly forecast ACC against the persistence anomaly forecast ACC. A persistence forecast was computed by maintaining the initiation month anomaly across all lead months.

Management strategy evaluation

To compare the performance of different harvest guidelines (HGs) including or excluding future environmental information, a management strategy evaluation (MSE) is employed (Punt and Donovan 2007). An MSE is a framework developed to test, through simulation modelling, the efficiency of alternative management procedures in achieving specific management goals, taking uncertainty into account (Punt and Donovan 2007). It consists of several elements. First, an *operating model* to simulate the dynamics of the fishery population is developed. The second component is the *management procedure*, where one simulates a management option, such as a harvest guideline, based on the perceived status of the fishery (Kell et al. 2005). Here, we assume that the perceived population is the same as the "true" sardine population from the operating model and do not introduce sampling or assessment errors or simulate a full stock assessment. The only sources of uncertainty are the process uncertainty arising from stochasticity in recruitment and that of the SST forecast. Finally, management ability to achieve specific objectives under each alternative management procedure is evaluated using *performance metrics* (Kell et al. 2005).

The operating model

The operating model is derived from the age-structured cohort model used in the risk evaluation framework for Pacific sardine (Hurtado-Ferro and Punt 2014, PFMC 2014); (see Appendix S1) for a more detailed description of the operating model. Recruits are simulated using an environmentally explicit Ricker stock–recruitment model following Jacobson and MacCall (1995) and Hurtado-Ferro and Punt (2014). While the current sardine management uses annual CalCOFI SST as a recruitment covariate, here, in recognition of the elevated forecast

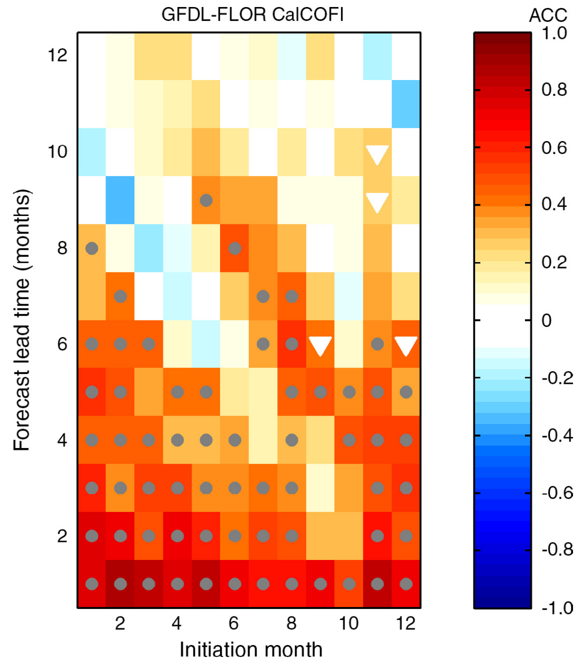

FIG. 2. Anomaly correlation coefficients (ACCs) as a function of forecast initialization month (x-axis) and lead time (y-axis) for the CalCOFI region. Initialization month 1 corresponds to 1 January. Gray dots indicate ACCs significantly above 0 at 5% level; white downward triangles indicate ACCs above persistence at 10% level.

skill from late winter to early summer (Fig. 2), the time period that is most important for sardine spawning and early larval survival (Lluch-Belda et al. 1991), we use March SST. This was selected as the best SST predictor among 12 late winter to early summer potential SST covariates using cross-validation, with the combined effects of spawning stock biomass and SST explaining 84% of the total recruitment variation (Appendix S1: Fig. S2). See Appendix S1 for details on the stock–recruitment model selection process.

As a test of operating model robustness, we verified the simulated spawning stock biomass (SB) with both 1981–2008 and 1945–1965 SB estimates from the stock assessment (Hill et al. 2010), and MacCall (1979), respectively. SB estimates were far less certain during this early period than more recent estimates, but extending back to 1945 offered an opportunity to assess the model's ability to simulate a population collapse (Appendix S1: Fig. S3).

The robustness of different management strategies was assessed by simulating, for each HG rule, the stock dynamics from 1945 to 2008, a time period that included low productivity conditions. As the hindcasts (re-forecasts) of SST predictions only start in 1982, the operating model was driven by observed SST at Scripps Pier plus a forecast error. Here we used the forecast error of the ensemble mean of a 1-February-initialized March SST forecast (2-months lead) as input into the operating model. Forecast error was computed as the standard deviation (SD) of the March SST forecast residuals from the 1982 to 2009 hindcast. For each HG, stock dynamics were simulated across 1000 realizations of stochastic variability in recruitment and SST forecast error, and tracking management performance statistics. At each time step, the recruitment errors and, for HG3 and HG4, forecast SST errors were randomly sampled from a normal distribution with SD equal to the SD of recruitment and SST prediction residuals, respectively.

Management procedure

The critical management decision assessed in this case study is each year's harvest guideline (i.e., catch limit in tons [Mg]) specified prior to the spring fishing season. Catch limits are set based on an estimate of the present biomass age 1 and older in tons at the beginning of the year (B_t) obtained from a stock assessment, and E_{msy}, the exploitation rate (harvested fraction of the stock per year) that would provide the maximum sustainable yield:

$$\mathrm{HG}_t = (B_t - 150000)E_{\mathrm{msy}}. \tag{1}$$

The HG for Pacific sardine also includes a 150000-ton harvest cutoff, which was incorporated into all the HGs considered here. Environmental effects on stock productivity can be incorporated into the HG via changes in recruitment that are reflected in the B_t estimate and/or via a temperature dependency of E_{msy}, as is currently done in the Pacific sardine HG (Hill et al. 2010). The temperature dependency of E_{msy}, depicted in Appendix S1: Fig. S4, results from the underlying SST-explicit stock recruitment function. The E_{msy}-SST relationship was developed following the procedure of Hurtado-Ferro and Punt (2014). Briefly, the operating model, which has a SST-explicit recruitment function (Appendix S1: Eq. S3), was projected forward for 1000 years for a range of exploitation rates under a constant March SST anomaly. This process was repeated for a range of SST anomalies, and for each SST anomaly the exploitation rate that produced the maximum mean catch was recorded. A polynomial model was then fit through the SST specific-maximum exploitation rates to obtain an E_{msy}–SST relationship (Appendix S1: Fig. S4).

The first HG rule, HG1, incorporated neither past nor future environmental information. E_{msy} was constant and set to 0.18. This was the constant exploitation rate from Hurtado-Ferro and Punt (2014) that maximized long-term catch under a stochastic recruitment error scenario. As in the current U.S. Pacific sardine HG, HG2 casts E_{msy} as a function of SST anomalies over the past 3 years (Fig. 1A). However, unlike the current Pacific sardine HG, we use March SST anomalies instead of annual SST. The third harvest guideline, HG3, moves the window of temperature anomaly forward to consider the two previous years and the predicted March SST conditions (Fig. 1B), which have a forecast error reflecting the prediction skill of a CM 2.5 FLOR March SST anomaly forecast at a 2-month lead time. The forecast error was sampled from a normal distribution with SD equal to those of the residuals between the observed and model hindcast SST. Thus, E_{msy} was computed as follows at each time step:

$$E_{\mathrm{msy}} = f(\mathrm{March\ SST}_{t-2\,\mathrm{to}\,t} + \varepsilon_{f2}) \quad \varepsilon_{f2} \sim N(0,\sigma_{f2}) \tag{2}$$

where σ_{f2} = 0.49, the SD of the 2-month lead forecast residuals.

The fourth HG, HG4, in addition to employing a dynamic E_{msy} informed by the SST prediction, also depended on an SST-dependent estimate of future stock biomass (Fig. 1C, Eq. 3).

$$\mathrm{HG}_t = \left(\frac{(B_t + B_{t+1})}{2} - 150000\right) E_{\mathrm{msy}}. \tag{3}$$

The temperature dependency of B_{t+1} derives from the prediction of recruits in year t, which is driven by the SST anomaly prediction. B_{t+1} is also dependent on catches in year t, determined by HG_t. Solving Eq. 2 after rewriting B_{t+1} as a function of HG_t yields

$$\mathrm{HG}_t = \left(\frac{(B_t + V_t)}{2} - 150000\right) \frac{1}{(1/E_{\mathrm{msy}}) + (e^{-M/2}/2)} \tag{4}$$

where V_t is the sum of B_t and recruit biomass in year t that survive natural mortality in year t, and M is the natural mortality, set at 0.4 yr^{-1}. Details of the derivation of Eq. 4 can be found in Appendix S1. Since V_t depends on a prediction of recruits in year t driven by the SST anomaly prediction, in addition to SST forecast uncertainty being reflected in E_{msy} as described for HG3 in Eq. 2, prediction uncertainty was reflected in the estimation of year t recruits. The predicted recruits used to compute V_t were generated as in Appendix S1: Eq. S3, but with SST set to

$$\mathrm{SST}_{f2} = \mathrm{SST}_{\mathrm{obs}} + \varepsilon_{f2} \quad \varepsilon_{f2} \sim N(0,\sigma_{f2}) \tag{5}$$

where σ_{f2} = 0.49, the SD of the 2-month lead forecast residuals.

Performance measures

We assessed the following performance metrics to evaluate the management performance of the different HGs: (1) mean and variability of yield and stock biomass; (2) probability of stock biomass falling below a 400,000 tons threshold; and (3) probability of yield falling below a 50000 tons threshold.

Metrics 2 and 3 reflect ecologically and economically important biomass or yield thresholds used in the Pacific sardine risk evaluation framework (PFMC 2014). The first reflects the minimum biomass necessary to sustain higher trophic levels in the ecosystem, the second the minimum yield required for an economically viable fishery. Variability of yield and stock biomass was measured by the population variability (PV) metric. PV is the average proportional difference between all combinations of values in a data series, and ranges between 0 and 1 (Heath 2006). Unlike SD or the coefficient of variation, PV is not biased by non-Gaussian behavior such as heavy tailed distributions characterized by many rare events or zero counts (Heath 2006).

Results and Discussion

Sea surface temperature anomaly predictions over the CalCOFI region showed significant skill over the sardine spawning period of January to July (Fig. 2). Skill, i.e., anomaly correlation coefficient (ACC) > 0.6, was commonly achieved for lead times of 1 or 2 months, extended out to 4 months in some cases, and mainly arose from the reliable persistence anomalies during this period (Fig. 2; Appendix S1: Fig. S5). We thus considered scenarios where harvest guidelines going into effect in spring may be informed by late winter SST anomaly predictions with 2-month leads.

The operating model of Pacific sardine dynamics was able to simulate the 1950s collapse, and provided an approximation of the true Pacific sardine dynamics (Appendix S1: Fig. S4). By capitalizing on more productive periods, all the HGs that included environmental information, either past or future, led to higher long-term yield than the constant exploitation rate in HG1 (Fig. 3A). When, as in HG3, SST prediction only informed E_{msy}, use of the SST anomaly prediction did not lead to an increase in yield as compared to HG2, which used only past SST observations (Fig. 3A). However, when the SST forecast was incorporated in both the E_{msy} estimate and the prediction of future biomass, the mean yield across realizations increased by 13% relative to HG2. The range of yields across all realizations overlapped, but only 14% of cases using HG4 produced yields below the mean of HG2.

While the average E_{msy} over the 64 years of simulation was comparable across HGs (Appendix S1: Fig. S6A), using a constant E_{msy}, as in HG1 led to more reactive decisions and a lower long-term yield. Severe reductions in catch limits only occurred once biomass declined or fell below the harvest cutoff (Appendix S1: Fig. S6B, C). By contrast, the SST informed HGs were more anticipatory, and reductions in catch limits followed declines in productivity more closely (Appendix S1: Fig. S6B, C).

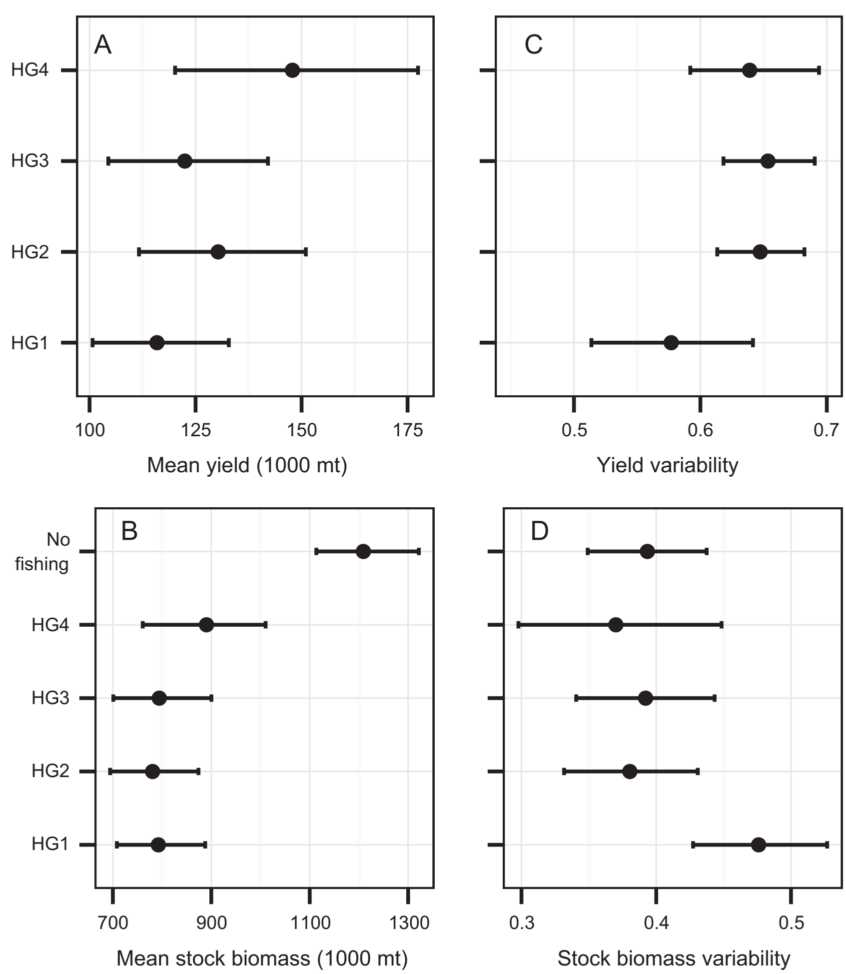

Fig. 3. Management performance metrics for the different harvest guidelines described in the methods. The HGs incorporating future SST information reflect the uncertainty of a 2-month lead forecast. Error bars show the 5-95th percentile range. 1000 mt = 1 Gg.

HG2–HG4 were also better able to take advantage of booms in productivity (Appendix S1: Fig. S6B, C).

It should be noted that a slight delay between reductions in catch limits and declines in productivity was still observed for HG2–HG4 as E_{msy} is based on a three-year running average of SST (Appendix S1: Fig. S6). The dependence on a running average was implemented to maintain a less variable catch, and hence less variable income, for fishers. Indeed, the more dynamic catch adjustments in HG2–HG4 led to higher yield variability than HG1 (Fig. 3C, D). It is important to note, however, that the larger yield variation in HG2–HG4 occurs around higher mean yields.

Integration of SST forecast information into E_{msy} further reduced the lag between productivity declines and reductions in catch limits (Appendix S1: Fig. S6). Nevertheless, there was no increase in yield in HG3, which uses a SST prediction informed E_{msy}, as compared to HG2 (Fig. 3A). It has been suggested that for short-lived species, such as Pacific sardine, long-term average yield could actually be highest when the implementation of an environment specific harvest rate is delayed by a few years (MacCall 2002), as in HG2. This allows for a faster rebuilding of the stock at the beginning of a favorable period, which may balance the fishing down of the stock at the beginning of a less productive one (MacCall 2002). On the other hand, by also integrating into the HG expected declines in stock biomass, as in HG4, the stock is not fished down at the beginning of a low productivity period. Thus, while biomass naturally declines because of environmental changes, the stock does not fall to as low a level.

The gain in yield with HG4 did not result in lower long-term mean stock biomass, which was also highest for HG4 (Fig. 3B). Furthermore, adoption of HG4 did not result in higher biomass variability as compared to the other HGs (Fig. 3C, D). In contrast to yield variability, biomass variability was highest for HG1. Indeed, under HG2–HG4, the probability of biomass falling below an ecologically acceptable threshold of 400000 tons was lower (Fig. 4A), and the fishery was closed less often (i.e., the probability of 0 catch was lower, Fig. 4C). Incorporation of environmental information allowed the stock to recover faster by curtailing fishing during the low-productivity phase. Even more promising, the increased yields that accompanied the proactive use of skillful seasonal SST forecasts in HG4 reduced the risk of falling below either biomass or yield thresholds by 27% and 5%, respectively, relative to HG2 (Fig. 4A, C).

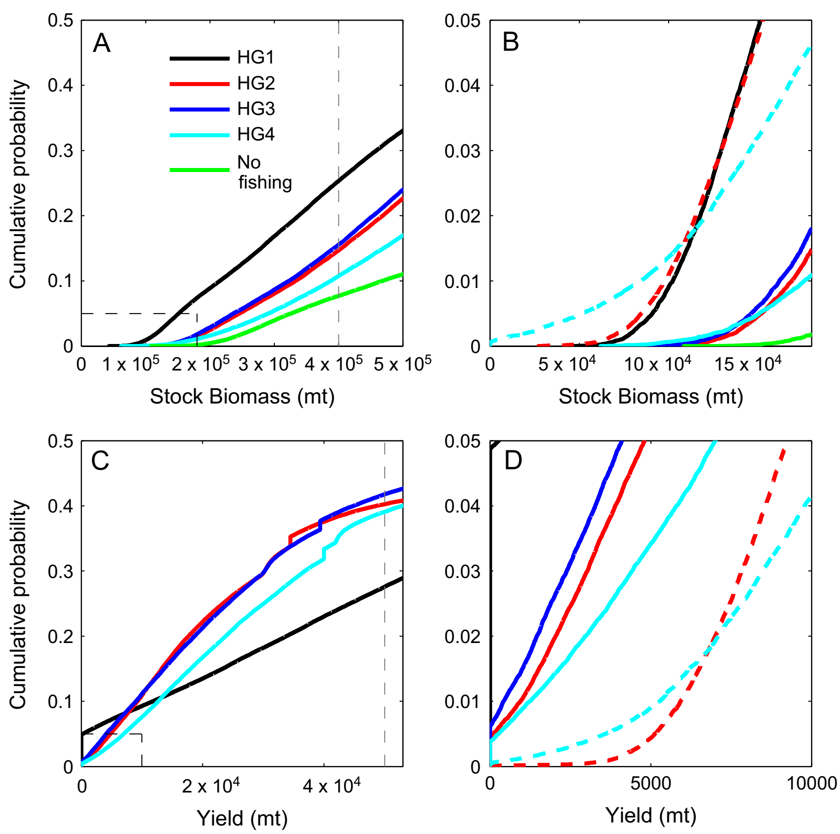

FIG. 4. Empirical cumulative distribution of simulated (A, B) stock biomass and (C, D) yield over the 64000 simulated time steps for harvest guidelines as described in the main text. Vertical dotted lines in panels A and C refer to ecologically and economically important thresholds of 400000 metric tons for biomass and 50000 metric tons for yield. Dotted rectangles in panels A and C delineate the area highlighted in the subsequent panel. Dotted lines in panels B and D represent the lower tails of the empirical cumulative distribution for HG2 (red) and HG4 (cyan) without the low biomass cutoff. 1 mt = 1 Gg.

We tested the robustness of the favorable results for HG4 in Figs. 3 and 4 to (1) removing the harvest cutoff, and (2) degraded SST anomaly forecast skill. A harvest cutoff restricting fishing during periods of low abundance has been shown to be effective in reducing probability of collapse, and in maintaining high stock biomass with little effect on long-term yield (Essington et al. 2015). When the harvest cutoff was removed, HG4 remained the best performing harvest rule for both yield and biomass (Appendix S1: Fig. S7). Improvements in management performance of the environmentally informed HGs as compared to HG1, the constant harvest rate HG, were even more dramatic, and HG1 was the worst performing rule also in terms of yield variability (Appendix S1: Fig. S7), as most HG1 runs resulted in a population collapse with no recovery. The inability of HG1 to curtail fishing rates during periods of low productivity led to fishing down of the stock. Removal of the cutoff, however, led to an increased probability of biomass falling to very low levels and of fisheries closures in HG4 relative to the less aggressive HG2 strategy (Fig. 4B, D, dashed lines). This highlights the value of complementing more aggressive use of forecast information with low biomass safeguards to prevent collapse in the event of an erroneous forecast.

Usefulness of a forecast is dependent on the timing of the management decision relative to the accuracy of the forecast at that time (Hobday et al. 2016). Stock assessments and associated catch decisions involve a lengthy review process, hence a long lead time may be required for the forecast information to be incorporated into catch target decisions. For example, the stock assessment detailing the 2011 HG was released in December 2010, but was initially reviewed by the scientific and statistical committee in October (Hill et al. 2010). However, the ability of HG4 to improve management performance as compared to HG2 deteriorated with decreasing SST forecast skill, with some of the HG4 realizations showing mean yields below even the lowest mean yield for HG2 when the deviation of the SST anomaly prediction residuals was >0.65°C (Fig. 5). For a springtime prediction in this region, such degradation of prediction skill occurs for lead times greater than 5 months. An October-initialized 6-month lead March SST forecast would hence be too uncertain to be included into a harvest recommendation. To take advantage of the improved management performance achieved when integrating accurate forecasts at short lead times, the management process would have to become more dynamic (Dunn et al. 2016), allowing for rapid, frequent revisions of HGs when accurate climate information becomes available as the stock assessment review process progresses until the final HG is released. Alternatively, future advances in climate prediction systems allowing for higher forecast skill at longer lead times would permit their integration into current management timeframes. We detail how this may be done in Fig. 6, but stress that, for this to be feasible, climate forecast skill has to be adequate when the management decision is made (Hobday et al. 2016).

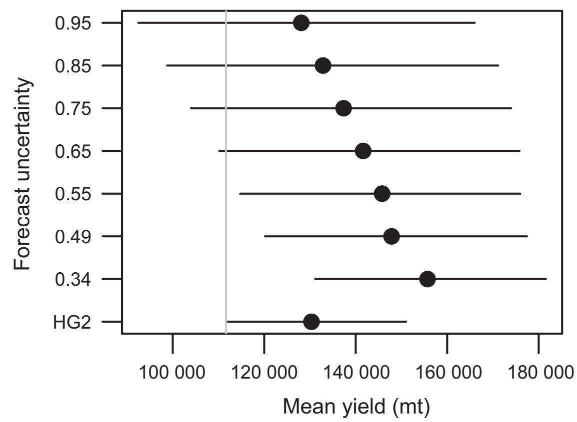

Fig. 5. Mean long-term yield across the 1000 realizations for HG4 with varying level of forecast uncertainty. Uncertainty refers to the SD of the residuals between the forecast and observed SST. Results from HG2 are included for comparison. The vertical gray line corresponds to the 5% percentile of the mean yield across the 1000 realizations computed for HG2. Error bars show the 5-95th percentile range.

Uncertainty in predicted fish stocks not only stems from the climate forecast, but also from the recruitment–environment relationship. In a hypothetical scenario, it was demonstrated that the environmental index has to explain at least ~50% of the variance in recruitment for it to be useful (De Oliveira and Butterworth 2005). Furthermore, unlike climate forecasts, which are obtained by a mechanistic model based on physical laws, recruitment–environment relationships are generally based on empirical statistical relationships. Such relationships may be spurious or non-stationary, and thus can break down over time (Myers 1998). While the relationship of Pacific sardine productivity with SST appears to be robust (Jacobson and MacCall 1995, Myers 1998, Deyle et al. 2013, Jacobson and McClatchie 2013, Lindegren and Checkley 2013), SST is likely not the proximate cause of recruitment fluctuations, but rather a proxy for complex changes in spawning habitat availability, trophic dynamics, larval retention, or a combination thereof (Lluch-Belda et al. 1991, Rykaczewski and Checkley 2008, Nieto et al. 2014). Our results are predicated upon the operating model, and hence on the assumption that SST is a robust indicator of changes in recruitment. If HG4 would be incorporated into the management framework, this relationship should be frequently tested, using cross validation methods (Francis 2006), to ensure its continued validity.

The results here presented assume that the observed abundance is equal to the true abundance, that is, we assume there is no assessment error. It was outside of the scope of the paper, but before introducing the proposed HG into the Pacific sardine assessment, future work will assess the robustness of these results to uncertainty in stock assessment. In particular, there is uncertainty in the

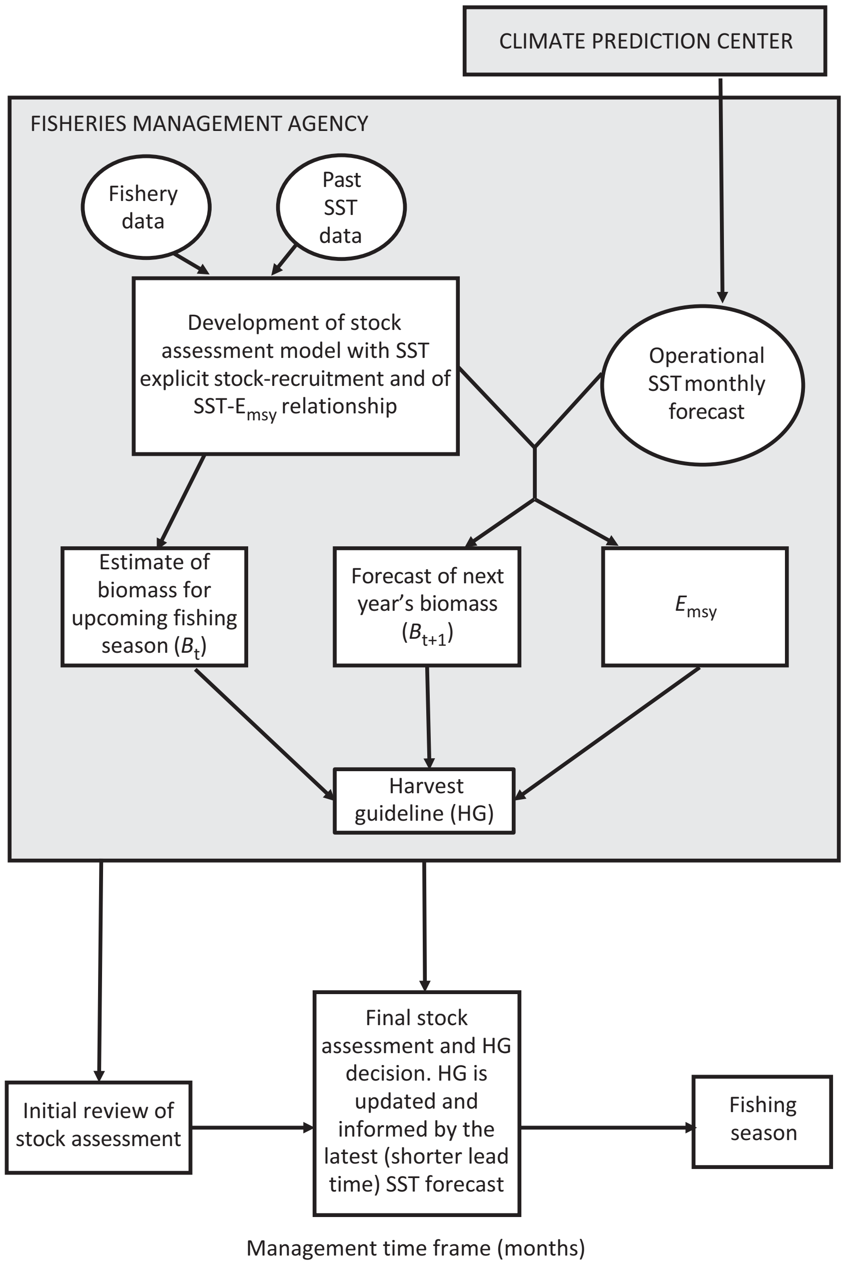

FIG. 6. Conceptual diagram outlining how the SST forecast would be implemented operationally into the fisheries management framework for HG4. See *Methods* for details on how B_t, B_{t+1}, and E_{msy} are computed. Note that monthly SST forecasts are already currently operational and released every month by climate prediction centers. They are available from http://www.cpc.ncep.noaa.gov/products/NMME/

terminal biomass estimate on which the current Pacific sardine HG is based (Hill et al. 2010). This stems from both estimation and structural uncertainty, which is manifested in the retrospective pattern observed for both biomass and recruitment estimates (Hill et al. 2010). Consideration of this source of uncertainty may further reduce differences between HG1, HG2, and HG3 if the differences in E_{msy} estimation are swamped by the large uncertainty in biomass. Furthermore, as the assessment error reflected in the biomass estimate may be further amplified in the biomass forecast informed by the SST prediction, the improvements in management performance here observed under HG4 may be reduced. To account for such uncertainty as well as feedbacks between assessment errors and state dynamics, future analyses will need to include the full Pacific sardine stock assessment model in the management strategy evaluation (Wiedenmann et al. 2015, Punt et al. 2016).

Conclusions

This study provides the first proof of concept of how climate forecasts may be used to inform the quintessential decision of fisheries managers: to assess how many fish to catch while maintaining long-term sustainability of the stock. Results show that a skillful climate forecast has the potential to make management of highly variable forage fish stocks more effective. Using future SST information to anticipate variations in biomass led to more effective catch targets. Improvements in average catch when the catch target is based on a short-term prediction of recruits have also been demonstrated for anchovy using hypothetical data and a hypothetical environment–recruitment relationship, as long as the environment is well predicted and the relationship between the environment and recruits robust (De Oliveira and Butterworth 2005). We have suggested it as achievable based on existing short-term SST forecasts and existing relationships between sardines and SST.

While the incorporation of climate forecast information into harvest guidelines appears promising, caution is also needed. Making a forecast implies being wrong some of the time. We show that combining forecast-informed harvest controls with additional harvest restrictions provides a means of modulating this risk. Furthermore, a robust relationship between recruitment and the environment has to be present, and be frequently retested while the underlying mechanisms driving recruitment change are investigated. Finally, forecast accuracy has to be high, and with a lead time adequate for the management time-frame. Future human population growth and climate change will place increased pressure on marine ecosystems (Rice and Garcia 2011). Seasonal climate forecasts, which are regularly made and distributed by many centers around the world, may provide an additional tool to better manage fish stocks in a variable environment and maintain their long-term resilience while not foregoing yield.

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