

Influence of temperature and upwelling intensity on Indian oil sardine (*Sardinella longiceps*) landings

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Introduction

Environmental variability is known to be a key driver of population variability of small forage fish such as sardines, anchovy and herring (Bakun 1996, Alheit and Hagen 1997, Cury et al. 2000, Checkley Jr. et al. 2017). In particular, ocean temperature and upwelling dynamics, along with density-dependent feedback, have been identified as important in affecting recruitment success and biomass of European and Pacific sardines (*Sardina pilchardus* and *Sardinops sagax*) (Jacobson and MacCall 1995, Rykaczewski and Checkley 2008, Alheit et al. 2012, Lindegren and Checkley Jr. 2012, Lindegren et al. 2013). Like other sardines, the Indian oil sardines show strong interannual fluctuations and larger decadal booms and busts. The Indian oil sardine offers an interesting case study to investigate the effects of environmental variability, particularly temperature and upwelling dynamics, as they occupy an ocean system that is warmer than that occupied by other sardines and have a strong seasonal cycle driven by the Indian summer monsoon.

The Indian oil sardine (*Sardinella longiceps* Valenciennes, 1847) is one of the most commercially important fish resources along the southwest coast of India (Figure 1) and historically has comprised approximately 25% of the catch biomass (Vivekanandan et al. 2003). Landings of the Indian oil sardine are highly seasonal and peak during and after the summer monsoon period (June through September), in conjunction with the onset and early relaxation of coastal upwelling. However, the landings of this small pelagic finfish are also highly variable from year to year. Small pelagics are well known to exhibit high variability in biomass due to the effects of environmental conditions on survival and recruitment (Bakun 1996, Alheit and Hagen 1997, Cury et al. 2000, Checkley Jr. et al. 2017). In this fishery, however, environmental conditions also affect exposure of sardines to the fishery. Until recently, the Indian oil sardine

fishery was artisanal and based on small human or low powered boats with no refrigeration. The fishery was confined to nearshore waters, and thus migration of fish schools in and out of the coastal zone greatly affected exposure to the fishery.

Researchers have examined a variety of environmental variables for their correlation with landings of the Indian oil sardine in order to understand the factors that drive landings variability. Precipitation during the southwest monsoon (Antony Raja 1969, 1974, Murty and Edelman 1971, Jayaprakash 2002) and the day of the monsoon arrival (Jayaprakash 2002) is thought to act as either a direct or indirect cue for spawning. Many studies have looked for correlations between precipitation, however the reported effects are positive in some studies and negative in others [Madhupratap et al. (1994);]. Researchers have also looked for and found correlations with various metrics of upwelling intensity, such as sea level at Cochin (Murty and Edelman 1971, Longhurst and Wooster 1990, Madhupratap et al. 1994, Jayaprakash 2002, Thara 2011), salinity and bottom sea temperature [Krishnakumar et al. (2008);], and with direct measures of productivity, such as nearshore zooplankton and phytoplankton abundance (Hornell 1910, Nair 1952, Nair and Subrahmanyam 1955, Madhupratap et al. 1994, George et al. 2012, Piontkovski et al. 2015, Menon et al. 2019). Researchers have also found correlations with near-shore sea surface temperature (SST); SST can affect both somatic growth rates and juvenile survival but also can cause fish to move off-shore and away from the shore-based fishery (Annigeri 1969, Prabhu and Dhulkhed 1970, Pillai 1991).

In this paper, we study the utility of environmental covariates to explain year-to-year variability in landings using the time series of quarterly Indian oil sardine landings from the SW coast of India. This time series is derived from a stratified sampling design that surveys landing sites along the coast and was first implemented in the 1950s (Srinath et al. 2005), however catch-at-length data are not available for the earlier years (prior to 2001) neither are stock size estimates nor fisheries independent data. A number of catch length studies are available but only for a small subset of years at specific landing sites. Thus traditional length- or age-structured models (e.g. Virtual Population Analysis) are not possible. Instead we use time-series models with covariates to model landings. Modeling and forecasting landings data (catch) using time-series models has a long tradition in fisheries and has been applied to many species (Mendelsohn 1981, Cohen and Stone 1987, Nobel and Sathianandan 1991, Stergiou and Christou 1996, Lloret et al. 2000, Georgakarakos et al. 2006, Prista et al. 2011, Lawer 2016), including oil sardines (Srinath 1998, Venugopalan and Srinath 1998). These models can be used to understand the variables associated with catch fluctuations and can be used to provide forecasts that assist fisheries planning. Unlike prior work on landings models with co-

variates, we use non-linear time-series models to allow a flexible effect of covariates and past catch on current landings. We also specifically focus on environmental covariates measured via remote-sensing. Remote-sensing data provide long time series of environmental data over a wide spatial extent at a daily and monthly resolution. In addition, a better understanding of how and whether remote sensing data explains variation in seasonal catch will support future efforts to use remote sensing data to improve catch forecasts.

Study Area

Our analysis focuses on the Kerala coast (Figure 1) region of India, where the majority of the Indian oil sardines are landed and where oil sardines comprise ca. 40% of the marine fish catch (Srinath 1998, Vivekanandan et al. 2003). This area is in the Southeast Arabian Sea (SEAS), one of world's major upwelling zones, with seasonal peaks in primary productivity driven by upwelling caused by winds during the Indian summer monsoon (Madhupratap et al. 2001, Habeebrehman et al. 2008) between June and September. Within the SEAS, the coastal zone off Kerala between 9°N to 13°N has especially intense upwelling due to the combined effects of wind stress and remote forcing (Smitha et al. 2008, Smitha 2010). The result is a strong temperature differential between the near-shore and off-shore and high primary productivity and chlorophyll in this region during summer and early fall (Madhupratap et al. 2001, Habeebrehman et al. 2008, Jayaram et al. 2010, Raghavan et al. 2010, Smitha 2010, Chauhan et al. 2011). The primary productivity peaks subside after September while mesozooplankton abundances increase and remain high in the inter-monsoon period (Madhupratap et al. 2001).

Oil sardine life cycle and fishery

The Indian oil sardine fishery is restricted to the narrow strip of the western India continental shelf, within 20 km from the shore (Figure 1). The yearly cycle (Figure 2) of the fishery begins at the start of spawning during June to July, corresponding with the onset of the southwest monsoon (Chidambaram 1950, Antony Raja 1969) when the mature fish migrate from offshore to coastal spawning areas. The spawning begins during the southwest monsoon period when temperature, salinity and suitable food availability are conducive for larval survival (Chidambaram 1950, Murty and Edelman 1971, Jayaprakash and Pillai 2000, Krishnakumar et al. 2008, Nair et al. 2016). Although peak spawning occurs in June to July, spawning continues into September (Hornell 1910, Hornell and Nayudu 1923, Antony Raja 1969, Prabhu and Dhulkhed 1970) and early- and late-spawning cohorts are evident in the length distributions

of the 0-year fish. Spawning occurs in shallow waters outside of the traditional range of the fishery (Antony Raja 1964), and after spawning the adults migrate closer to the coast and the spent fish become exposed to the fishery.

After eggs are spawned, they develop rapidly into larvae within 24 hrs (Nair 1959). The phytoplankton bloom that provide sardine larvae food is dependent upon nutrient influx from coastal upwelling and runoff from rivers during the summer monsoon and early fall. The blooms start in the south near the southern tip of India in June, increase in intensity and spread northward up the coast (Smitha 2010). Variation in the bloom initiation time and intensity leads to changes in the food supply and to corresponding changes in the growth and survival of larvae and in the later recruitment of 0-year sardines into the fishery (George et al. 2012). Oil sardines grow rapidly during their first few months, and 0-year fish (40mm to 100mm) from early spawning appear in the catch in August and September in most years (Antony Raja 1970, Nair et al. 2016). As the phytoplankton bloom spreads northward, the oil sardines follow, and the oil sardine fishery builds from south to north during the post-monsoon period. Oil sardines remain inshore feeding throughout the winter months, until March to May when the inshore waters warm considerably and sardines move off-shore to deeper waters (Chidambaram 1950). Catches of sardines are correspondingly low during this time for all size classes. The age at first maturity occurs at approximately 150 mm size (Nair et al. 2016), which is reached within one year. When the summer monsoon returns, the oil sardine cycle begins anew.

Overall, catches along the Kerala coast are fairly high throughout the year except during quarter 2 March-May (Figure 3). The age-distribution caught by the fishery varies through the year. The fishery is closed during June to mid-July during the monsoon and peak spawning, and when it resumes in mid-July, it is first dominated by 1-2.5 year old mature fish (Bensam 1964, Antony Raja 1969, Nair et al. 2016). In August or September a spike of 0-year (40mm) juveniles from the June spawning typically appears in the catch (Antony Raja 1969, Nair et al. 2016) and another spike of 0-year fish is sometimes seen in February from the late fall spawning (Prabhu and Dhulkhed 1967, 1970). From October through July, the catch is dominated by fish from 120mm-180mm (Antony Raja 1970, Prabhu and Dhulkhed 1970, Nair et al. 2016) which is a mix of 0-year, 1-year and 2-year fish (Nair et al. 2016, Rohit et al. 2018).

Materials and Methods

Sardine landing data

Quarterly fish landing data have been collected by the Central Marine Fisheries Research Institute (CMFRI) in Kochi, India, since the early 1950s using a stratified multi-stage sample design that takes into account landing centers, number of fishing days, and boat net combinations in fishing operations (Srinath et al. 2005). The quarterly landings for oil sardine landed from all gears in Kerala were obtained from CMFRI reports (1956-1984) and online databases (1985-2015) (CMFRI 1969, 1995, 2016, Pillai 1982, Jacob et al. 1987). The quarterly landing data were log-transformed to stabilize the seasonal variance.

Remote-sensing data

We analysed monthly composites of the following environmental data derived from satellites: sea surface temperature (SST), chlorophyll-a (CHL), upwelling (UPW) and precipitation. The monthly means of the covariate time series are shown in Figure 4.

For sea surface temperature, we used Advanced Very-High Resolution Radiometer (AVHRR) data, which provides accurate nearshore SST values. Although the ICOADS product provides SST values for earlier years, ICOADS does not provide accurate nearshore temperatures. For 1981 to 2003, we used the Pathfinder Version 5.2 product on a 0.0417 degree grid. These data were developed by the Group for High Resolution Sea Surface Temperature (GHRSSST) and served by the US National Oceanographic Data Center. For 2004 to 2016, we used the NOAA CoastWatch SST products derived from NOAA's Polar Operational Environmental Satellites (POES). For chlorophyll-a, we used the chlorophyll-a products developed by the Ocean Biology Processing Group in the Ocean Ecology Laboratory at the NASA Goddard Space Flight Center. For 1997 to 2002, we used the chlorophyll-a 2014.0 Reprocessing (R2014.0) product from the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) on the Orbview-2 satellite. These data are on a 0.1 degree grid. For 2003 to 2017, we used the MODIS-Aqua product on a 0.05 degree grid. These CHL data are taken from measurements by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Aqua Spacecraft. The SST and CHL data were averaged across thirteen 1 degree by 1 degree boxes which roughly parallel the bathymetry (Figure 1). The SST and CHL satellite data were retrieved from the NOAA ERDDAP server (Simons 2017).

For an index of coastal upwelling, we used the sea-surface temperature differential between near shore and 3 degrees offshore as described by Naidu et al. (1999) and Smitha et al. (2008). The index was computed as the average SST in box 4 off Kochi (Figure 1) minus the average SST in box 13. For SST, we used the remote-sensing sea-surface temperature data sets described above. This SST-based upwelling index has been validated as a more reliable metric of upwelling off the coast of Kerala compared to wind-based upwelling indices (Smitha et al. 2008). The SST-based upwelling index and chlorophyll-a blooms are strongly correlated (Figure 5).

Precipitation data were obtained from two different sources. The first was an estimate of the monthly precipitation (in mm) over Kerala from land-based rain gauges (Kothawale and Rajeevan 2017); these data are available from the Indian Institute of Tropical Meteorology and the data are available from the start of our landing data (1956). The second was a remote-sensing precipitation product from the NOAA Global Precipitation Climatology Project (Adler et al. 2016). This provides estimate of precipitation over the ocean using a global 2.5 degree grid. We used the 2.5 by 2.5 degree box defined by latitude 8.75 to 11.25 and longitude 73.25 to 75.75 for the precipitation off the coast of Kerala. These data are available from 1979 forward (NCEI 2017). The land and nearshore ocean precipitation data are highly correlated (Appendix), supporting the use of the land time series as a proxy for the precipitation over the ocean off the Kerala coast.

Hypotheses

Our statistical analyses were structured around specific hypotheses (Table 1) concerning which remote-sensing covariates in which months should correlate with landings in specific quarters. These hypotheses were based on biological information concerning how environmental conditions affect sardine survival and recruitment and affect exposure of Indian oil sardines to the coastal fishery. The quarter 3 (Jul-Sep) catch overlaps the summer monsoon and the main spawning months. This is also the quarter where small 0-year fish from early spawning (June) often appear in the catch, sometimes in large numbers. Variables that affect or are correlated with movement of sardines inshore should be correlated with quarter 3 landings. In addition, pre-spawning (January-May) environmental conditions should be correlated with the spawning strength as adult oil sardines experience an acceleration of growth during this period along with egg development. The post-monsoon catch (Oct-May) is a mix of 0-year fish (less than 12 months old) and mature fish (greater than 12 months old). Variables that are correlated with

larval and juvenile survival should correlate with the post-monsoon catch both in the current year and in future years, one to two years after.

Our hypotheses (Table 1) focus mainly on two drivers: upwelling and ocean temperature. We also test hypotheses concerning precipitation as this has historically been an environmental covariate considered to influence the timing of oil sardine landings. Salinity has been proposed as responsible for spawning initiation; however we do not have long-term salinity data. In the Appendix, we show tests of chlorophyll-a but as with salinity the CHL time series is short (1997-2015) and the tests have low power.

Explanatory models

We modeled the catches during the late-spawning season (quarter 3, July-September) separately from the post-monsoon season (October-March). Thus there is no seasonality in our catch time series, as we analyzed a yearly time series of quarter 3 catches separately from a yearly time series of post-monsoon catches. We divided the catch in this way for biological and statistical reasons. Catch in quarter 3 (July-September) captures a mix of spawning age fish as it overlaps with the tail end of the spawning season, is affected by a fishery closure from July to mid-August during the summer monsoon, and is periodically inflated by the appearance of small 0-year fish from early summer spawning. In addition, the covariates that affect the timing of spawning, movement of post-spawning mature fish inshore, and early egg and larval survival may be different than those that affect later growth, survival and shoaling that exposes fish to the inshore fishery. Analyzing catch and covariate time series without seasonality also had an important statistical benefit—we removed the problem of seasonality in the catch and all the covariates. The oil sardine life-cycle is seasonal and driven by the strong seasonality in this monsoon influenced system. A simple statistical model with quarters will explain much of the quarterly catch data since most of the yearly variability is due to seasonality and any environmental covariate with a similar seasonality will also show high correlation with the landings. Our goal was to explain year-to-year variability thus eliminating the confounding effect of seasonality in the data was important.

We tested ARIMA models on both quarter 3 and post-monsoon catch time series and found little support for auto-regressive errors (ARIMA models with a MA component) based on diagnostic tests of the residuals and model selection. The best supported ARIMA models were simple AR models ($x_t = bx_{t-1} + \eta_t$). This lack of strong autocorrelation in residuals has been found in other studies that tested ARIMA models for forecasting small pelagic catch

(Stergiou and Christou 1996). We thus used AR-only models, however we tested both linear and non-linear models using a generalized additive model (GAM) of the form $x_t = s(x_{t-1}) + \eta_t$. The landings models were fit using conditional sum of squares (conditioning on the first 1 or 2 landings values in the time series). We investigated correlations between environmental variables and sardine catch using generalized additive models (GAMs, Wood 2017) to allow one to model the effect of a covariate as a flexible non-linear function. It was known that the effects of the environmental covariates were likely to be non-linear, albeit in an unknown way. Our approach is analogous to that taken by Jacobson and MacCall (1995) in a study of the effects of SST on Pacific sardine recruitment.

The first step in our analysis was to determine the catch model: the model for current catch as a function of the past catch. One feature of GAMs is that they allow the smoothing parameter of the response curve to be estimated. However we fixed the smoothing parameter at an intermediate value so that reasonably smooth responses were achieved and to limit the flexibility of the models being fit. Multi-modal or overly flexible response curves would not be realistic for our application. We used GAMs with smooth terms represented by penalized regression splines (Wood 2011, using the mgcv package in R) and fixed the smoothing term at an intermediate value (sp=0.6).

Our catch models took the form

- random walk: $\ln(C_{i,t}) = \alpha + \ln(C_{j,t-1}) + \varepsilon_t$
- AR-1: $\ln(C_{i,t}) = \alpha + \phi_1 \ln(C_{j,t-1}) + \varepsilon_t$
- AR-2: $\ln(C_{i,t}) = \alpha + \phi_1 \ln(C_{j,t-1}) + \phi_2 \ln(C_{k,t-2}) + \varepsilon_t$
- non-linear: $\ln(C_{i,t}) = \alpha + s_1(\ln(C_{j,t-1})) + s_2(\ln(C_{k,t-2})) + \varepsilon_t$

where $\ln(C_{i,t})$ is the log catch in the current year t in season i . We modeled two different seasons: 3rd quarter catch $C_{m,t}$ (July-September) which is during the late part of the summer monsoon and post-summer monsoon catch $C_{p,t}$ (October-June). The catches were logged to stabilize and normalize the variance. $s()$ is a non-linear function estimated by the GAM algorithm. The model is primarily statistical, meaning it should not be thought of as being a population growth model. We tested models with prior year post-summer monsoon catch ($C_{p,t-1}$) and 3rd quarter catch ($C_{m,t-1}$) as the explanatory catch variable. The catch models were fit to 1982 to 2015 catch data, corresponding to the years where the SST, upwelling and precipitation data were available. F-tests and AIC on nested sets of models (Wood et al. 2016) were used to evaluate the support for the catch models and later for the covariate models.

After selection of the best model with the 1982-2015 data, the fitting was repeated with the 1956-1981 and 1956-2015 catch data to confirm the form of the catch models.

Once the catch models were determined, the covariates were studied individually and then jointly. As with the catch models, F-tests and AIC on nested sets of GAM models were used to evaluate the support for models with covariates. The smoothing term was fixed at an intermediate value ($sp=0.6$) instead of treated as an estimated variable. Our models for catch with covariates took the form

$$\ln(C_{i,t}) = M + s_1(V_{1,t}) + s_2(V_{2,t}) + \varepsilon_t$$

where M was the best catch model from step 1. The covariate model seeks to explain unexplained variance in the the catch model via a linear or non-linear function of the covariates, V_1 and V_2 . The covariates tested are those discussed in the section on covariates that have been hypothesized to drive the size of the sardine biomass exposed to the fishery.

Results

Catches in prior seasons as explanatory variables

Models with $\ln(N_{t-1})$ or $\ln(S_{t-1})$ as a covariate were strongly supported over the “naive” model: the “last year’s catch” model (Table 2, time-dependency test). The “naive” model has no estimated parameters and is a standard null model for time series modeling. There was support for including the post-summer monsoon catch in the previous year as an explanatory variable for the quarter 3 catch. Post-monsoon catch in the prior year was more supported as an explanatory covariate than quarter 3 catch in the prior year. Addition of the catch two years prior, $\ln(N_{t-2})$ or $\ln(S_{t-2})$, did not reduce AIC and for $\ln(N_{t-2})$ led to either no decrease in the residual error (MASE) or an increased the residual error for the model with linearity (Table 2, Linearity test). Addition of $\ln(S_{t-2})$ did decrease the residual errors, but the was not warranted given the increased number of estimated parameters based on AIC. We also tested the support for non-linearity in the effect of the prior year catch on the quarter 3 catch. This was done by comparing models with $\ln(N_{t-1})$ or $\ln(S_{t-1})$ included as a linear term or as a non-linear function $s()$ (Table 2, Linearity test). The residual error decreased using a non-linear response at the cost of 1.4 degrees of freedom. The result was only weak (non-significant) support for allowing a non-linear response based on AIC and the F-test. The full set of models tested,

including tests using catch during the spawning months in previous seasons as a covariate are shown in Tables A1 and A2. The results were the same if we used the full landings data set from 1956 to 2015 (Table A3). Overall, the landings in prior seasons was only weakly explanatory for the quarter 3 catch, and the maximum adjusted R^2 for these models was less than 30% (Table 2).

The results on model structure were similar for models of the landings (N_t) during the post-summer monsoon months (Table 3), but the models explained more of the variance. The most supported model for N_t (Table 3) used a non-linear response to landings during the post-monsoon months of the previous season $\ln(N_{t-1})$ with a non-linear response to quarter 3 landings two years prior $\ln(S_{t-2})$. There was low support for including landings earlier than two seasons prior or for using the quarter 3 landings during in the immediately prior season (Tables A4, A5, and A6). We did not test models for the October-June catch using the quarter 3 (July-September) catch in the current fishing season, so immediately prior. These data would not be available in a forecasting setting as the data require 12 months to process.

Environmental covariates as explanatory variables

There was no support for using precipitation during the summer monsoon (June-July) or pre-monsoon period (April-May) as an explanatory variable for the catch during quarter 3 (Table B1) nor the non-spawning months (Table B2). This was the case whether precipitation in the current or previous season was used, if precipitation was included as non-linear or non-linear effect, or if the smoothing term (degree of non-linearity allowed) was estimated and thus not constrained, and if either precipitation during monsoon (June-July) or pre-monsoon (April-May) were used as the covariate. Quarter 3 overlaps with the spawning period and precipitation is often thought to trigger spawning, however we were unable to find any consistent association of catch during these spawning and early-post spawning months with precipitation.

However, we found significant correlation between average SST during the early post-spawning period (July-September) and quarter 3 catch during the spawning season (Table 3, Table B3). Sea surface temperature has been found to be correlated with sardine recruitment in a number of other studies [Jacobson and MacCall (1995); add the others]. The residual error was lowest in a model with SST in both the prior year and two years prior included and with a non-linear response for both (Appendix). This a similar result to Jacobson and MacCall (1995) who found that SST in multiple prior years was supported as explanatory variables for sardine recruitment and productivity. However the reduction in degrees of freedom was high for this

model and it was not supported based on AIC. The model with the lowest AIC was a model with only a non-linear response of current year July-September SST. The response shows a step-response with a negative effect at low temperatures and then an increased effect at higher temperatures (Figure 6). This type of step-response has been found in studies of the effect of SST on recruitment in Pacific sardines (Jacobson and MacCall 1995). In our case, the SST effect is for the same months as the catch thus the effect is associated either with spawning or movement of mature fish into the nearshore area (where they are exposed to the fishery). The R^2 for this model was 0.37 (Table 4).

eeh: this is not right. Need to fix. The strongest predictor of the catch during quarter 3 however was the upwelling strength during January-March (4-6 months prior) in the previous season (Tables 4 and B4). January-March is the period when adults are preparing for spawning, however January-March is a period when the young of the year and age-1 fish would be found feeding in large shoals in the coastal region and this time of year has the second highest catches and catches that are dominated by small-sized fish (*citation*). The best supported model included only the upwelling strength in the prior year, without SST included as a covariate (Table 4). The R^2 for this model was 0.60 and the fitted versus observed catches for this model are shown in Figure 7.

eeh: this is not right. Need to fix. For catch in the post-summer monsoon months (Oct-Jun), sea surface temperature during July to September in the current season was a significant predictor similar to what was found for catches in the spawning months (quarter 3). Upwelling in the prior season was also a significant predictor, but the important months were Oct-Dec. This is period is important for larval and early juvenile survival and growth, and other studies have also found this to be a critical period for future stock size in sardines (*citation*). The model with the lowest residual variance and lowest AIC was the model which included both the SST and upwelling covariates (Table 4). The R^2 for this model was 0.73 and the fitted versus observed catches for this model are shown in Figure 7.

Chlorophyll-a density is speculated to be an important predictor of larval sardine survival and growth. In addition, sardines shoal in response to coastal chlorophyll blooms, which brings them in contact with the coastal fisheries. Thus chlorophyll-a density is assumed to be an important driver of future or current sardine catches. We had chlorophyll-a remote-sensing data only from 1998 onward. Our simplest covariate model required 5 degrees of freedom, thus we were limited in the analyses we could conduct. In addition, the years, 1998-2014, have relatively low variability in catch sizes; the logged catch sizes during this period range from 10-11 during quarter 3 and 11-12 during the other three quarters. Second degree polynomial

models were fit (Appendix C) to the average log chlorophyll-a density in the current and prior season from quarter 3 (Jul-Sep), 4 (Oct-Dec), and 1 (Jan-Mar). Chlorophyll-a density was not a significant predictor for the spawning catch for any of the tested combinations of current or prior season and quarter. The only significant effect was seen for post-summer monsoon catches using chlorophyll-a density in Oct-Dec of the current and prior season (Table C1). This matches results which found that the upwelling index in October-December of the prior season was a predictor for the post-summer monsoon catch. The SST-based upwelling index and chlorophyll-a density are both indices of low-trophic level productivity.

Discussion

I am still trying to decide how to write the discussion. How does this relate to other work on sardines and esp the correlation between SST and landings?

Sardines in all the world's ecosystems exhibit large fluctuations in abundance (Baumgartner et al. 1992, Schwartzlose et al. 2010). These small forage fish are strongly influenced by natural variability in upwelling driven by both large-scale forces, i.e. El Nino patterns, and by changes in winds and currents and in addition local conditions of temperature, salinity, and oxygen levels have both direct and indirect on sardine recruitment and survival.

Many studies on Pacific sardines have looked at the correlation between sea surface temperature (SST) and recruitment. Temperature can have direct effect, an indirect effect on food availability or affect survival (Houde 1987). Studies in the California Current System, have found that SST explains year-to-year variability in Pacific sardine recruitment (Jacobson and MacCall 1995, Checkley Jr. et al. 2009, 2017, Lindegren and Checkley Jr. 2012). Consistent with these studies, we also found that SST was the covariate that explained variability in catch anomalies (difference between the landing prediction from prior years' catches).

McClatchie et al. (2010) found no SST relationship with SST and Pacific sardine recruitment, however their analysis used a linear relationship while both other studies that found a relationship (Jacobson and MacCall 1995, Checkley Jr. et al. 2017) allowed a non-linear relationship. Both Jacobson and MacCall (1995) and Checkley et al (2017) found a step-like response function for temperature, where lower temperatures were poor and had negative effects and then at a threshold value the effect became positive. Our analysis found a similar step-like effect function.

There were three outlier years when catch were much lower than expected based on prior

catches. For these years, sea surface temperature improved the model fit greatly (Figure 8).

Remote sensing satellites can be used to detect changes in ocean physical, biological and chemical properties, such as surface temperature, winds, surface height, surface waves, rainfall and surface salinity, as well as the ecosystem and water quality changes. Using these covariates to improve landing forecasts has the potential to improve fisheries management for small pelagics (Tommasi et al. 2016). However, improving forecasts using these covariates is not obvious. We found no improvement in forecasts over a simple model using a non-linear effect of past catch using many of the covariates known to be associated with spawning, growth and survival: precipitation, upwelling indices, and chlorophyll-a.

Nonetheless, remote-sensing derived chlorophyll, SST and SSH estimates have been used to estimate sardine habitat of the west coast of the USA (Zwolinski et al. 2011). In India, satellite measurements of chlorophyll have been used to predict high densities of oil sardines. This is used a functional tool for producing forecasts for fisherman and has lead to increases in their efficiency (catch per unit effort) (*citation*). The weak performance of our upwelling covariates may be due to the coarse correspondence between the temperature differential and other aspects of upwelling intensity that are critical to oil-sardines—the spatial extent both along the coast and off the coast and the timing of the start of upwelling.

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Figure Legends

Figure 1. Close up of Kerala State with the latitude/longitude boxes used for the satellite data. Kerala State is marked in grey and the oil sardine catch from this region is being modeled.

Figure 3. Quarterly catch data 1956-2014 from Kerala. The catches have a strong seasonal pattern with the highest catches in quarter 4 Note that quarter 3 is July-Sept and that the fishery is closed July 1 to Aug 15, thus the fishery is only open 1.5 months in quarter 3. The mean catch (metric tonnes) in quarters 1 to 4 are 38, 19.2, 30.9, and 59.9 metric tonnes respectively.

Figure 2. The sardine life-cycle in the SE Indian Ocean and how it interacts with the fishery.

Figure 4. Remote sensing covariates used in the analysis. All data are monthly averages over Box 4 in Figure 1 on the Kerala coast off of Kochi. Panel A) Upwelling Index. The upwelling index is the difference between the near-shore sea surface temperature (SST) and the off-shore SST defined as 3 degrees longitude offshore. Panel B) Surface chlorophyll-a (CHL). The CHL data are only available from 1997 onward. Panel C) Sea surface temperature constructed from Advanced Very High Resolution Radiometer (AVHRR). Panel D) Average daily rainfall (mm/day) off the Kerala coast.

Figure 5. Key oil sardine life-history events overlaid on the monthly SST in the near-shore and off-shore and the near-shore CHL.

Figure 6. Effects of covariates estimated from the GAM models. Panel A) Effect of SST during the spawning months (Jul-Sep) on catch during the spawning months. Low SST is associated with lower than expected catch during the spawning months. Panel B) Effect of upwelling (inshore/off-shore SST differential) during Jan-Mar of the prior season on catch during the next spawning months (Jul-Sep). The index is the difference between offshore and inshore SST, thus a negative value indicates warmer coastal surface water than off-shore. Warm coastal water during Jan-Mar when sardines are foraging along the coast, is associated with lower catch during the next spawning season. Panel C) Effect of SST during the spawning months (Jul-Sep) on catch during the subsequent non-spawning months (Oct-Jun). Low SST is associated with lower than expected catch during the following non-spawning months. Panel D) Effect of upwelling (inshore/off-shore SST differential) during Oct-Dec of the prior season on catch during the non-spawning months (Oct-Jun) the next season. Strong upwelling (positive upwelling index) in the early larval and juvenile period (Oct-Dec) is associated with higher than expected catch in the next season.

Figure 8. Fitted versus observed catch with models with and without environmental covariates. Panel A) Fitted versus observed log catch in the spawning months with only non-spawning catch in the previous season as the covariate: $S_t = s(N_{t-1}) + \varepsilon$. Panel B) Fitted versus observed log catch in the spawning months with Jan-Mar upwelling in the prior season added as a covariate to the model in panel A. This model was: $S_t = s(N_{t-1}) + s(V_{t-1}) + \varepsilon$. Panel C) Fitted versus observed log catch in the non-spawning months with only non-spawning catch in the previous season and spawning catch two season prior as the covariates: $N_t = s(N_{t-1}) + s(S_{t-2}) + \varepsilon$. Panel D) Fitted versus observed log catch in the non-spawning months with current season SST in Jul-Sep (V) and Oct-Dec upwelling in the prior season (W) added as covariates. This model was $N_t = s(N_{t-1}) + s(S_{t-2}) + s(V_t) + \beta W_{t-1} + \varepsilon$. W was added linearly since the data were insufficient to estimate four non-linear effects.

Table 1. Hypotheses for covariates affecting landings. S_t is quarter 3 (July-September) catch in the current season, S_{t-1} is quarter 3 catch in the previous season. N_t is the post-monsoon October-March catch in the current season and N_{t-1} is the October-March catch in the prior season. Because the fishing season is July-June, N_t spans two calendar years.

Stage	Hypothesis	Resp.	Covariates
Age 2+	DD1. S_t is dominated by mature age 2+ fish, thus abundance of the 1-yr and 2-yr ages in the prior season (Oct-Mar catch) should be correlated with the abundance of mature fish this year.	S_t	N_{t-1}
Age 1-2	DD2. Abundance of 1-yr and 2-yr fish should be correlated with strength of the cohorts from the previous two seasons. The quarter 3 catch, dominated by mature fish, in the prior two years is expected to be correlated with post-monsoon catch.	N_t	S_{t-1} and S_{t-2}
Age 2+	DD3. Because age 2 fish appear in the post-monsoon catch, we also expect the post-monsoon catch (dominated by age 1 and 2) in the previous season to be correlated with the post-monsoon catch in the current season. Post-monsoon catch two seasons prior should be minimally correlated with current post-monsoon catch.	N_t	N_{t-1}
Spawn	S1. The onset of monsoon precipitation triggers movement of adults from offshore to spawning areas due to changes in salinity, turbulence or noise. Spent adults migrate inshore and are exposed to the fishery.	S_t	Seasonal precipitation anomaly during Jun-Jul in year t
Spawn	S2. The level of precipitation in pre-monsoon months predicts spawning strength.	S_t	Seasonal precipitation anomaly during Apr-May in year t
Spawn	S3. Low SST is associated with delayed and limited spawning as a behavioral response by adults to avoid exposing larvae to low temperatures associated with poor survival. Conversely, high SST is indicative of poor upwelling and poor larval feeding conditions.	S_t	Average SST during Jun-Sep in year t
Spawn	S4. xtremely high upwelling brings poorly oxygenated water and very low temperatures to the surface causing sardines to move offshore where they are less exposed to the ²⁴ fishery.	S_t	Average upwelling index Jun-Sep, Max upwelling index Jun-Sep in year t

Table 1. Continued.

Stage	Hypothesis	Resp.	Covariates
Larv.	L1. Highest somatic growth occurs in Sep-Oct. Larval growth and survival is higher in warmer water. Low SST at this time is also associated with strong upwelling which advects larvae into offshore waters where productivity is lower.	N_t	Average SST during Sep-Oct in year t-1
Juv.	L2. Upwelling is associated with higher productivity and higher density of zooplankton, which leads to better larval and juvenile growth and survival. Thus the strength of upwelling during the monsoon should be associated with higher biomass in subsequent years. At the same time, extremely strong upwelling brings poorly oxygenated water to the surface causing larval mortality and advects larvae offshore.	N_t and S_t	Ave. upwelling index Jun-Sep and max upwelling index Jun-Sep in year t-1 and t-2
Juv.	L3. Chlorophyll blooms are signatures of high productivity from nutrient influx either due to upwelling or coastal inputs. Bloom intensity in prior years should be associated with future sardine biomass.	N_t and S_t	Ave. Chl-a density Jun-Dec in year t-1 and t-2
All ages	A1. During the Mar-Apr, the sea temperatures are high and sardines migrate offshore to avoid high temp.	Catch Q2 year t	Ave. SST Q2 year t, max SST Q2 year t
All ages	A1. The changes brought about by the El Niño Southern Oscillation (ENSO) cycle have a variety of effect on environmental parameters (precipitation, SST, thermal fronts, Wind) which impacts spawning and early survival. This in turn impacts the overall abundance.	N_t and S_t	ONI year t-1

Table 2. Model selection tests of time-dependency and linearity for the quarter 3 (Jul-Sep) catch model using F-tests of nested models fit to log of landings data. S_t is the quarter 3 catch of season t . N_{t-1} is the post-monsoon Oct-Mar catch in the prior sardine season. N_{t-2} is the same for two seasons prior. $s()$ is a non-linear function of the response variable. MASE is mean absolute squared error of the residuals. The tests are nested and the numbers before the models indicates the nest level. In the list with numbers 1, 2, 3a, 3b, two nested tests were done, one on 1, 2, 3a and one on 1, 2, 3b. See tables in Appendix A for the full set of time-dependency and linearity tests.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Naive Model 1982-2015 data						
$\ln(S_t) = \ln(S_{t-1}) + \varepsilon_t$	34		1			129.25
AR-1 Model						
$\ln(S_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	32	0.832				120.01
Time dependency test						
1. $\ln(S_t) = \alpha + \ln(N_{t-1}) + \varepsilon_t$	33	0.9	10.6			118.8
2. $\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	32	0.836	20	4.77	0.037	115.93
3a. $\ln(S_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(N_{t-2}) + \varepsilon_t$	31	0.841	17.5	0.03	0.868	117.9
3b. $\ln(S_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(S_{t-2}) + \varepsilon_t$	31	0.812	18.8	0.52	0.475	117.36
Linearity test						
1. $\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	32	0.836	20			115.93
2. $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	30.6	0.81	21.7	1.12	0.323	116.12
3a. $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + s(\ln(N_{t-2})) + \varepsilon_t$	28.3	0.809	18.7	0.29	0.776	118.99
3b. $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + s(\ln(S_{t-2})) + \varepsilon_t$	27.7	0.769	23.1	1.02	0.397	117.53

Table 3. Model selection tests for the N_t model using AIC for models fit to log landings data. S_t is the catch during the spawning season (Jul-Sep). N_t is the catch during the non-spawning period (Oct-Jun) of season t ; note the fishing season is defined as Jul-Jun not calendar year. S_{t-1} and N_{t-1} are the catch during the prior sardine season during and after the spawning period respectively. S_{t-2} and N_{t-2} are the same for two seasons prior.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Naive Model 1982-2015 data						
$\ln(N_t) = \ln(N_{t-1}) + \varepsilon_t$	33	0.594				94.58
AR-1 Model						
$\ln(N_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	31	0.583	38			91.68
$\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	29.6	0.516	47	5.16	0.021	87.71
$\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(N_{t-2})) + \varepsilon_t$	27.4	0.479	47	1.14	0.341	88.99
$\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	26.5	0.445	57	9.08	0.008	82.46

Table 4. Top covariates for the S_t (Jul-Sep catch) and N_t (Oct-Jun catch) models. The models are nested; the roman numeral indicates the level of nestedness. Models at levels II and higher are shown with the component that is added to the base level model (M0 or M1) at top. The full set of covariate models tested are given in Appendix B. The fitted versus observed catches from the covariate models are shown in Figure 8.

Model	Residual df	Residual deviance	F	p value	AIC
Jul-Sep catch models with covariates					
V_t = Jul-Sep SST current season					
W_{t-1} = Jan-Mar upwelling prior season					
I-M0: $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon$ $(R^2 adj = 22\%, \text{Var}(\varepsilon) = 1.59)$	29.6	47.85			113.82
II: $\ln(S_t) = M0 + s(V_t)$ $(R^2 adj = 34\%, \text{Var}(\varepsilon) = 1.33)$	27	37.26	3.09	0.052	109.73
III: $\ln(S_t) = M0 + s(V_t) + s(W_{t-1})$ $(R^2 adj = 35\%, \text{Var}(\varepsilon) = 1.33)$	24.4	34.21	0.87	0.459	111.22
II: $\ln(S_t) = M0 + s(W_{t-1})$ $(R^2 adj = 20\%, \text{Var}(\varepsilon) = 1.62)$	26.9	45.18	0.6	0.605	116.35
Oct-Jun catch models with covariates					
V_t = Jul-Sep SST current season					
W_{t-1} = Oct-Dec upwelling prior season					
I-M1: $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + s(\ln(S_{t-2})) + \varepsilon$ $(R^2 adj = 57\%, \text{Var}(\varepsilon) = 0.59)$	25.6	15.69			80.76
II: $\ln(N_t) = M1 + s(V_t)$ $(R^2 adj = 74\%, \text{Var}(\varepsilon) = 0.36)$	23.2	8.76	7.82	0.002	66.14
III: $\ln(N_t) = M1 + s(V_t) + \beta W_{t-1}$ $(R^2 adj = 74\%, \text{Var}(\varepsilon) = 0.36)$	22.2	8.49	0.8	0.375	67.06
II: $\ln(N_t) = M1 + s(W_{t-1})$ $(R^2 adj = 57\%, \text{Var}(\varepsilon) = 0.6)$	23.4	14.8	0.66	0.541	82.56

Appendices

Appendix A: Tests for prior season catch as covariate

Table A1. Model selection tests of time-dependency the log catch during spawning months using F-tests of nested linear models. S_t is the catch during the spawning period (Jul-Sep). N_t is the catch during the non-spawning period (Oct-Jun). S_{t-1} and N_{t-1} are the catch during the prior season during and after the spawning period respectively. S_{t-2} and N_{t-2} are the same for two seasons prior. Test A uses catch during the spawning period as the explanatory variable. Test B uses catch during the non-spawning period as the explanatory variable. The numbers in front of the model equation indicate the level of nestedness. For Test C, there are two nested model sets, each with a different model 3.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Time dependency test A 1983-2015 data						
1. $\ln(S_t) = \alpha + \ln(S_{t-1}) + \varepsilon_t$	32	1.03	-29.1			128.5
2. $\ln(S_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	31	0.855	9.8	15.28	0	117.63
3. $\ln(S_t) = \alpha + \beta_1 \ln(S_{t-1}) + \beta_2 \ln(S_{t-2}) + \varepsilon_t$	30	0.852	12.7	2.05	0.163	117.45
Time dependency test B 1983-2015 data						
1. $\ln(S_t) = \alpha + \ln(N_{t-1}) + \varepsilon_t$	32	0.908	11			116.24
2. $\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	31	0.852	20	4.48	0.043	113.65
3. $\ln(S_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(N_{t-2}) + \varepsilon_t$	30	0.857	17.4	0.04	0.846	115.61
Time dependency test C 1983-2015 data						
1. $\ln(S_t) = \alpha + \ln(N_{t-1}) + \varepsilon_t$	32	0.908	11			116.24
2. $\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	31	0.852	20	4.49	0.043	113.65
3. $\ln(S_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(S_{t-1}) + \varepsilon_t$	30	0.86	17.6	0.09	0.768	115.55
3. $\ln(S_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(S_{t-2}) + \varepsilon_t$	30	0.836	18.6	0.47	0.496	115.13

Table A2. Model selection tests of time-dependency the catch during spawning months using non-linear responses instead of linear responses as in Table A1 See Table A1 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Time dependency test A 1983-2015 data						
$\ln(S_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	31	0.855	9.8			117.63
$\ln(S_t) = \alpha + s(\ln(S_{t-1})) + \varepsilon_t$	29	0.834	19.9	2.73	0.085	115.01
$\ln(S_t) = \alpha + s_1(\ln(S_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	26.2	0.814	20.2	0.86	0.466	116.82
Time dependency test B 1983-2015 data						
$\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	31	0.852	20			113.65
$\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	29.6	0.821	21.7	1.12	0.321	113.82
$\ln(S_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(N_{t-2})) + \varepsilon_t$	27.3	0.816	18.9	0.36	0.732	116.58
Time dependency test C 1983-2015 data						
$\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	29.6	0.821	21.7			113.82
$\ln(S_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-1})) + \varepsilon_t$	26.9	0.743	26.7	1.59	0.218	113.58
$\ln(S_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	26.8	0.785	23.4	1.06	0.381	115.07

Table A3. Model selection tests of time-dependency for the catch during spawning months using 1956-2015 data. See Table A1 for definitions.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Time dependency test B linear 1956-2015 data						
$\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	56	0.832	11.7	8.38	0.005	181.63
$\ln(S_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(N_{t-2}) + \varepsilon_t$	55	0.833	10.1	0.02	0.896	183.61
Time dependency test B non-linear 1956-2015 data						
$\ln(S_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	56	0.832	11.7			181.63
$\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	54.3	0.831	11.2	0.52	0.566	183.05
$\ln(S_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(N_{t-2})) + \varepsilon_t$	51.7	0.827	8.6	0.2	0.872	186.72

Table A4. Model selection tests of time-dependency the N_t model using F-tests of nested models fit to 1983 to 2014 log landings data. The years are determined by the covariate data availability and end in 2014 since the landings data go through 2015 and N_{2014} includes quarters in 2014 and 2015. N_t is the catch during the non-spawning period (Qtrs 4 and 1: Oct-Mar) of season t (Jul-Jun). S_{t-1} and N_{t-1} are the catch during the prior sardine season during and after the spawning period respectively. S_{t-2} and N_{t-2} are the same for two seasons prior. Test A uses catch during the spawning period as the explanatory variable. Test B uses catch during the non-spawning period as the explanatory variable. Test C uses both. The numbers next to the model equations indicate the level of nestedness.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Naive Model 1983-2014 data						
$\ln(N_t) = \ln(N_{t-1}) + \varepsilon$	32	0.607				92.73
Time dependency test A 1983-2014 data						
1. $\ln(N_t) = \alpha + \ln(S_{t-1}) + \varepsilon_t$	31	0.836	-19.4			109.82
2. $\ln(N_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	30	0.628	26.3	20.34	0	95.34
3. $\ln(N_t) = \alpha + \beta_1 \ln(S_{t-1}) + \beta_2 \ln(S_{t-2}) + \varepsilon_t$	29	0.619	26.8	1.21	0.281	96.03
Time dependency test B 1983-2014 data						
1. $\ln(N_t) = \alpha + \ln(N_{t-1}) + \varepsilon_t$	31	0.607	25.5			94.73
2. $\ln(N_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	30	0.599	37.5	6.74	0.015	90.05
3. $\ln(N_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(N_{t-2}) + \varepsilon_t$	29	0.595	35.4	0.03	0.861	92.02
Time dependency test C 1983-2014 data						
1. $\ln(N_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	30	0.599	37.5			90.05
2a. $\ln(N_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(S_{t-1}) + \varepsilon_t$	29	0.59	35.6	0.11	0.746	91.93
2b. $\ln(N_t) = \alpha + \beta_1 \ln(N_{t-1}) + \beta_2 \ln(S_{t-2}) + \varepsilon_t$	29	0.599	35.4	0.01	0.923	92.04

Table A5. Model selection tests of time-dependency the N_t model using non-linear responses instead of linear responses as in Table A4 See Table A4 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Time dependency test A 1983-2014 data						
$\ln(N_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	30	0.628	26.3			95.34
$\ln(N_t) = \alpha + s(\ln(S_{t-1})) + \varepsilon_t$	28.1	0.613	30	1.72	0.2	94.94
$\ln(N_t) = \alpha + s_1(\ln(S_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	25.1	0.579	36.6	1.84	0.167	93.76
Time dependency test B 1983-2014 data						
$\ln(N_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	30	0.599	37.5			90.05
$\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	28.6	0.533	45.9	4.06	0.042	86.3
$\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(N_{t-2})) + \varepsilon_t$	26.4	0.493	46.1	0.87	0.443	87.71
Time dependency test C 1983-2014 data						
$\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	28.6	0.533	45.9			86.3
$\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-1})) + \varepsilon_t$	26	0.521	44.6	0.58	0.615	88.93
$\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	25.6	0.454	57.3	3.43	0.032	80.76

Table A6. Table A5 with 1956-2015 data instead of 1983 to 2014 data. See Table A4 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
Time dependency test A 1956-2015 data						
1. $\ln(N_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	55	0.539	16.7			151.42
2. $\ln(N_t) = \alpha + s(\ln(S_{t-1})) + \varepsilon_t$	53.4	0.54	17.5	1.03	0.352	151.96
3. $\ln(N_t) = \alpha + s_1(\ln(S_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	50.7	0.528	16.8	0.64	0.576	154.46
Time dependency test B 1956-2015 data						
1. $\ln(N_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	55	0.536	30.4			141.2
2. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	53.3	0.523	32.4	1.7	0.197	140.6
3. $\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(N_{t-2})) + \varepsilon_t$	50.8	0.511	32.1	0.72	0.521	142.77
Time dependency test C 1956-2015 data						
1. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	53.3	0.523	32.4			140.6
2a. $\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-1})) + \varepsilon_t$	50.9	0.515	33.4	1.13	0.339	141.63
2b. $\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	50.7	0.506	31.8	0.65	0.563	143.07

Table A7. Model selection tests for the N_t model using AIC for models fit to log landings data with catch during the spawning season S_t added as a covariate. Data 1983 to 2014 were used.

Model	Residual df	Residual deviance	AIC	NA	NA	NA
Time dependency test A 1956-2015 data						
1. $\ln(N_t) = \alpha + \beta \ln(S_{t-1}) + \varepsilon_t$	55	0.539	16.7			151.42
2. $\ln(N_t) = \alpha + s(\ln(S_{t-1})) + \varepsilon_t$	53.4	0.54	17.5	1.03	0.352	151.96
3. $\ln(N_t) = \alpha + s_1(\ln(S_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	50.7	0.528	16.8	0.64	0.576	154.46
Time dependency test B 1956-2015 data						
1. $\ln(N_t) = \alpha + \beta \ln(N_{t-1}) + \varepsilon_t$	55	0.536	30.4			141.2
2. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	53.3	0.523	32.4	1.7	0.197	140.6
3. $\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(N_{t-2})) + \varepsilon_t$	50.8	0.511	32.1	0.72	0.521	142.77
Time dependency test C 1956-2015 data						
1. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	53.3	0.523	32.4			140.6
2a. $\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-1})) + \varepsilon_t$	50.9	0.515	33.4	1.13	0.339	141.63
2b. $\ln(N_t) = \alpha + s_1(\ln(N_{t-1})) + s_2(\ln(S_{t-2})) + \varepsilon_t$	50.7	0.506	31.8	0.65	0.563	143.07

Appendix B: Tests for environmental variables as covariates

Table B1. Model selection tests of GPCP precipitation as an explanatory variable for the catch during spawning months (Jul-Sep) using 1983 to 2015 data. The data range is determined by the years for which SST was available in order to use a consistent dataset across covariate tests. S_t is the catch during Jul-Sep of season t . V_t is the covariate in the current season which spans two calendar years from July to June in the next year. V_{t-1} is the covariate in the prior Jul-Jun season.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1983-2015 data						
1. $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	29.6	0.821	21.7			113.82
V_t = Jun-Jul Precipitation						
2. $\ln(S_t) = M + \beta V_t$	28.6	0.786	21.6	0.93	0.341	114.73
3. $\ln(S_t) = M + s(V_t)$	26.8	0.778	23.7	1.08	0.347	114.89
4. $\ln(S_t) = M + s(V_t) + \beta V_{t-1}$	25.9	0.783	21.7	0.26	0.606	116.51
5. $\ln(S_t) = M + s(V_t) + s(V_{t-1})$	24.2	0.766	19.6	0.29	0.712	118.23
V_t = Apr-May Precipitation						
2. $\ln(S_t) = M + \beta V_t$	28.6	0.817	21.9	1.03	0.319	114.61
3. $\ln(S_t) = M + s(V_t)$	26.8	0.793	20.3	0.35	0.685	116.31
4. $\ln(S_t) = M + s(V_t) + \beta V_{t-1}$	25.8	0.774	17.7	0.1	0.751	118.15
5. $\ln(S_t) = M + s(V_t) + s(V_{t-1})$	24.1	0.773	17.9	0.72	0.476	118.93

Table B3. Model selection tests of sea surface temperature off Cochi as the explanatory variable (V) for the catch during spawning months (Jul-Sep) using 1983 to 2015 data. See Table B1 for an explanation of the models.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
1. $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	29.6	0.821	21.7			113.82
$V_t = \text{Jul-Sep SST}$						
2. $\ln(S_t) = M + \beta V_t$	28.6	0.77	23.7	2.14	0.156	113.81
3. $\ln(S_t) = M + s(V_t)$	27	0.639	34.5	3.72	0.047	109.73
4. $\ln(S_t) = M + s(V_t) + \beta V_{t-1}$	26.1	0.608	35.5	1.46	0.236	110
5. $\ln(S_t) = M + s(V_t) + s(V_{t-1})$	24.7	0.593	35.7	0.75	0.437	110.58
$V_t = \text{Jan-Dec SST}$						
2. $\ln(S_t) = M + \beta V_t$	28.6	0.849	23.5	1.67	0.209	113.95
3. $\ln(S_t) = M + s(V_t)$	26.7	0.849	20.3	0.11	0.894	116.44
4. $\ln(S_t) = M + s(V_t) + \beta V_{t-1}$	25.7	0.842	20.7	1.17	0.286	117.02
5. $\ln(S_t) = M + s(V_t) + s(V_{t-1})$	24	0.791	21.8	0.95	0.39	117.49

Table B4. Model selection tests of upwelling intensity off Cochi as the explanatory variable. See Table B1 for an explanation of the models.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
1. $\ln(S_t) = \alpha + s(\ln(N_{t-1})) + \varepsilon_t$	29.6	0.821	21.7			113.82
V_t = Jul-Sep Upwelling current and prior seasons						
2. $\ln(S_t) = M + \beta V_t$	28.6	0.765	26	2.55	0.124	112.83
3. $\ln(S_t) = M + s(V_t)$	26.7	0.762	23.9	0.3	0.736	114.91
4. $\ln(S_t) = M + s(V_t) + \beta V_{t-1}$	25.7	0.767	21.2	0	0.947	116.81
5. $\ln(S_t) = M + s(V_t) + s(V_{t-1})$	24	0.756	19.7	0.44	0.622	118.42
V_t = Oct-Dec Upwelling prior season						
2. $\ln(S_t) = M + \beta V_{t-1}$	28.6	0.834	19.9	0.3	0.586	115.46
3. $\ln(S_t) = M + s(V_{t-1})$	27.2	0.825	18	0.18	0.753	117.01
V_t = Jan-Mar Upwelling prior season						
2. $\ln(S_t) = M + \beta V_{t-1}$	28.6	0.845	20.3	0.46	0.5	115.3
3. $\ln(S_t) = M + s(V_{t-1})$	26.9	0.826	20.2	0.68	0.496	116.35

Table B5. Model selection tests of GPCP precipitation as an explanatory variable for the catch during the non-spawning months (Oct-Jun) using 1983 to 2014 data. The data range is determined by the years for which SST was available in order to use a consistent dataset across covariate tests. N_t is the catch during Oct-Mar of season t . V_t is the covariate in the current season (current season spans two calendar years from July to June in the next year). V_{t-1} is the covariate in the prior season. M is the base model without environmental covariates. The model sets are nested and the number before the equation indicates the level of nestedness.

Model		Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1983-2014 data							
1. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + s(\ln(S_{t-2})) + \varepsilon_t$		25.6	0.454	57.3			80.76
$V_t = \text{Jun-Jul Precipitation}$							
2. $\ln(N_t) = M + \beta V_t$		24.7	0.446	59.4	2.32	0.142	79.97
3. $\ln(N_t) = M + s(V_t)$		23	0.441	58.3	0.3	0.699	81.59
4. $\ln(N_t) = M + \beta V_{t-1}$		24.7	0.454	55.6	NA	NA	82.77
5. $\ln(N_t) = M + s(V_{t-1})$		22.8	0.432	57.8	1.42	0.263	82.14
$V_t = \text{Apr-May Precipitation}$							
2. $\ln(N_t) = M + \beta V_t$		24.7	0.452	55.9	0.13	0.717	82.56
3. $\ln(N_t) = M + s(V_t)$		22.9	0.46	54.8	0.31	0.704	84.23
4. $\ln(N_t) = M + \beta V_{t-1}$		24.6	0.453	55.7	NA	NA	82.75
5. $\ln(N_t) = M + s(V_{t-1})$		23	0.449	55	0.46	0.601	84.03

Table B6. Model selection tests of sea surface temperature off Cochi as the explanatory variable (V_t) for the catch during the non-spawning months (Oct-Jun) using 1983 to 2014 data. See Table B5 for an explanation of the models.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1983-2014 data						
1. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + s(\ln(S_{t-2})) + \epsilon$	25.6	0.454	57.3			80.76
V_t = Jan-Dec SST						
2. $\ln(N_t) = M + \beta V_t$	24.7	0.45	64.9	6.64	0.017	75.3
3. $\ln(N_t) = M + s(V_t)$	22.9	0.448	63.8	0.28	0.731	77.15
4. $\ln(N_t) = M + \beta V_{t-1}$	24.7	0.449	57	0.82	0.369	81.8
5. $\ln(N_t) = M + s(\ln(S_{t-2})) + s(V_{t-1})$	22.9	0.434	59.7	1.68	0.21	80.62
V_t = Jul-Sep SST						
2. $\ln(N_t) = M + \beta V_t$	24.7	0.455	65.8	10.69	0.004	74.42
3. $\ln(N_t) = M + s(V_t)$	23.2	0.383	74.2	6.18	0.011	66.14
4. $\ln(N_t) = M + \beta V_{t-1}$	24.7	0.452	56	0.16	0.682	82.48
5. $\ln(N_t) = M + s(\ln(S_{t-2})) + s(V_{t-1})$	23.3	0.44	57.2	1.23	0.296	82.25

Table B7. Model selection tests of upwelling intensity off Cochi as the explanatory variable. See Table B5 for an explanation of the models.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1983-2014 data						
1. $\ln(N_t) = \alpha + s(\ln(N_{t-1})) + s(\ln(S_{t-2})) + \varepsilon$	25.6	0.454	57.3			80.76
V_t = Jul-Sep Upwelling						
2. $\ln(N_t) = M + \beta V_t$	24.7	0.47	60.9	3.55	0.073	78.71
3. $\ln(N_t) = M + s(V_t)$	22.9	0.456	61.1	0.81	0.444	79.47
4. $\ln(N_t) = M + \beta V_{t-1}$	24.7	0.458	57.4	1.04	0.316	81.43
5. $\ln(N_t) = M + s(\ln(S_{t-2})) + s(V_{t-1})$	22.9	0.461	55.5	0.12	0.864	83.79
V_t = Oct-Dec Upwelling						
2. $\ln(N_t) = M + \beta V_t$	24.7	0.448	56.4	0.43	0.509	82.19
3. $\ln(N_t) = M + s(V_t)$	23.3	0.438	56.6	0.73	0.444	82.77
4. $\ln(N_t) = M + \beta V_{t-1}$	24.7	0.476	57.8	1.28	0.268	81.18
5. $\ln(N_t) = M + s(\ln(S_{t-2})) + s(V_{t-1})$	23.4	0.468	56.8	0.2	0.721	82.56
V_t = Jan-Mar Upwelling						
2. $\ln(N_t) = M + \beta V_t$	24.7	0.467	56.3	0.35	0.549	82.26
3. $\ln(N_t) = M + s(V_t)$	23.1	0.458	56.4	0.75	0.455	82.98
4. $\ln(N_t) = M + \beta V_{t-1}$	24.7	0.45	55.8	0.04	0.828	82.68
5. $\ln(N_t) = M + s(\ln(S_{t-2})) + s(V_{t-1})$	23	0.45	54.1	0.13	0.843	84.73

Appendix C: Tests for Chlorophyll-a as a covariate

Table C2. Model selection tests of Chlorophyll-a (CHL) as an explanatory variable for the Jul-Sep catch (S_t) using 1998 to 2014 data. The data range is determined by the years for which CHL was available. V_t is CHL in the current season which spans two calendar years from July to June in the next year. V_{t-1} is CHL in the prior Jul-Jun season. Only CHL in Oct-Dec and Jan-Mar in the prior season is used since for the current season, these months are after the Jul-Sep catch being modeled. Non-linearity is modeled as a 2nd-order polynomial due to data constraints and appears as $p()$ in the model equations. The Jul-Sep catch is modeled as a function of Oct-Jun catch in the prior year only, without Jul-Sep catch 2-years prior as in the other covariate analyses (Appendix B). This is done due to data constraints. The models are nested; the Roman numeral indicates the level of nestedness. Models at levels II and higher are shown with the component that is added to the base level model (M) at top.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1998-2014 data						
1. $\ln(S_t) = \alpha + p(\ln(N_{t-1})) + \varepsilon$	14	0.271	26.5			18.94
V_t = Jul-Sep Chlorophyll						
2. $\ln(S_t) = M + \beta V_t$	13	0.227	25.6	0.86	0.377	18.97
3. $\ln(S_t) = M + p(V_t)$	12	0.231	19.9	0.06	0.808	20.87
4. $\ln(S_t) = M + p(V_t) + \beta V_{t-1}$	11	0.242	15.2	0.32	0.586	22.35
5. $\ln(S_t) = M + p(V_t) + p(V_{t-1})$	10	0.244	8.3	0.17	0.687	24.05
V_t = Oct-Dec Chlorophyll						
2. $\ln(S_t) = M + \beta V_{t-1}$	13	0.243	20	0.08	0.789	20.19
3. $\ln(S_t) = M + p(V_{t-1})$	12	0.212	18.2	0.71	0.416	21.22
V_t = Jan-Mar Chlorophyll						
2. $\ln(S_t) = M + \beta V_{t-1}$	13	0.246	20.8	0.19	0.672	20.03
3. $\ln(S_t) = M + p(V_{t-1})$	12	0.247	15	0.12	0.74	21.87

Table C1. Model selection tests of Chlorophyll-a (CHL) as an explanatory variable for Oct-Jun catch (N_t) using 1998 to 2014 data. The data range is determined by the years for which CHL was available. V_t is CHL in the current season which spans two calendar years from July to June in the next year. V_{t-1} is CHL in the prior Jul-Jun season. Non-linearity is modeled as a 2nd-order polynomial due to data constraints and appears as $p()$ in the model equations. The Oct-Jun catch is modeled as a function of Oct-Jun catch in the prior year only, without Jul-Sep catch 2-years prior as in the other covariate analyses (Appendix B). This was done due to data constraints. The models are nested; the Roman numeral indicates the level of nestedness. Models at levels II and higher are shown with the component that is added to the base level model (M) at top.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1998-2014 data						
1. $\ln(N_t) = \alpha + p(\ln(N_{t-1})) + \varepsilon$	14	0.271	26.5			18.94
V_t = Jul-Sep Chlorophyll						
2. $\ln(N_t) = M + \beta V_t$	13	0.271	21.6	0.1	0.756	20.8
3. $\ln(N_t) = M + p(V_t)$	12	0.265	23.7	1.18	0.303	20.96
2. $\ln(N_t) = M + \beta V_{t-1}$	13	0.27	21.2	0.05	0.829	20.88
3. $\ln(N_t) = M + p(V_{t-1})$	11.6	0.27	14.7	0.03	0.935	22.87
V_t = Oct-Dec Chlorophyll						
2. $\ln(N_t) = M + \beta V_t$	13	0.275	21.7	0.16	0.695	20.76
3. $\ln(N_t) = M + p(V_t)$	12	0.254	20.6	0.95	0.353	21.65
4. $\ln(N_t) = M + p(V_t) + \beta V_{t-1}$	11	0.218	38.3	4.04	0.072	17.88
5. $\ln(N_t) = M + p(V_t) + p(V_{t-1})$	10	0.217	32.1	0	0.951	19.88
2. $\ln(N_t) = M + \beta V_{t-1}$	13	0.242	38.7	3.83	0.078	16.61
3. $\ln(N_t) = M + p(V_{t-1})$	10.4	0.222	39.6	0.82	0.499	17.51
V_t = Jan-Mar Chlorophyll						
2. $\ln(N_t) = M + \beta V_t$	13	0.282	23.9	0.45	0.516	20.29
3. $\ln(N_t) = M + p(V_t)$	12	0.277	19.3	0.24	0.632	21.92
2. $\ln(N_t) = M + \beta V_{t-1}$	13	0.254	28.5	1.27	0.284	19.23
3. $\ln(N_t) = M + p(V_{t-1})$	11	0.252	22.2	0.18	0.832	21.53

Table C3. Model selection tests of Chlorophyll-a as an explanatory variable for the catch during the non-spawning months (Oct-Jun) using box 5.

Model	Residual df	MASE	Adj. R2	F	p value	AIC
base model (M) 1998-2014 data						
1. $\ln(N_t) = \alpha + p(\ln(N_{t-1})) + \epsilon$	14	0.271	26.5			18.94
V_t = Jul-Sep Chlorophyll						
2. $\ln(N_t) = M + \beta V_t$	13	0.25	36.2	2.58	0.139	17.28
3. $\ln(N_t) = M + p(V_t)$	12	0.245	31.1	0.03	0.866	19.23
2. $\ln(N_t) = M + \beta V_{t-1}$	13	0.271	22.4	0.26	0.623	20.62
3. $\ln(N_t) = M + p(V_{t-1})$	10.5	0.253	25.1	0.96	0.43	21.14
V_t = Oct-Dec Chlorophyll						
2. $\ln(N_t) = M + \beta V_t$	13	0.26	33.3	2.68	0.133	18.05
3. $\ln(N_t) = M + p(V_t)$	12	0.237	34	1.25	0.29	18.5
4. $\ln(N_t) = M + p(V_t) + \beta V_{t-1}$	11	0.186	45.3	3.16	0.106	15.83
5. $\ln(N_t) = M + p(V_t) + p(V_{t-1})$	10	0.186	39.8	0	0.985	17.83
2. $\ln(N_t) = M + \beta V_{t-1}$	13	0.224	43.5	4.88	0.049	15.23
3. $\ln(N_t) = M + p(V_{t-1})$	11.1	0.214	39.9	0.3	0.738	17.12
V_t = Jan-Mar Chlorophyll						
2. $\ln(N_t) = M + \beta V_t$	13	0.25	35.9	3.14	0.107	17.36
3. $\ln(N_t) = M + p(V_t)$	12	0.246	34.6	0.77	0.4	18.35
2. $\ln(N_t) = M + \beta V_{t-1}$	13	0.256	24.1	0.84	0.38	20.25
3. $\ln(N_t) = M + p(V_{t-1})$	10.4	0.207	50.8	3.46	0.062	14

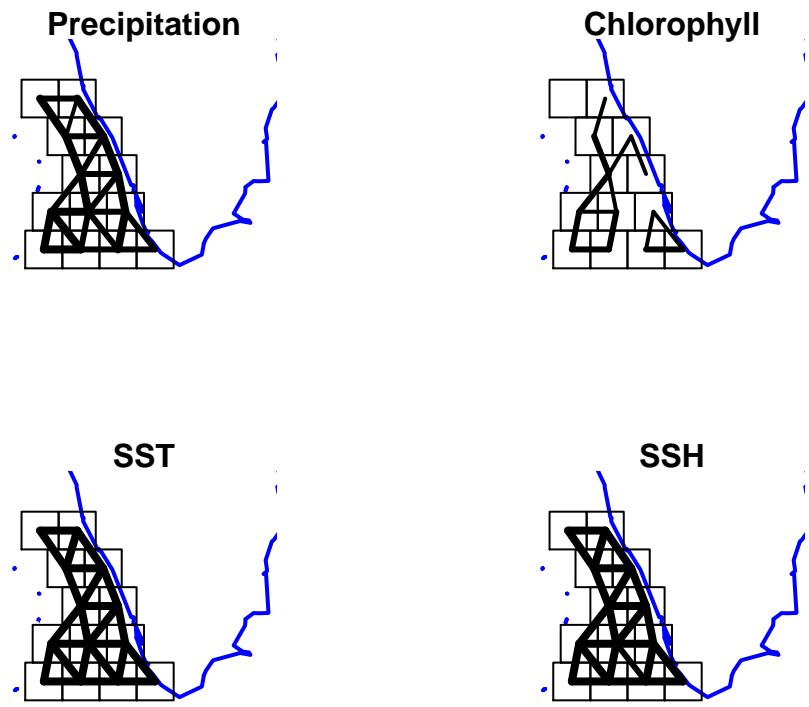


Figure C1. Correlation of the covariates across boxes. Correlation is shown by the width of the lines between neighboring boxes.

Appendix D: Correlation of covariates across the boxes

Appendix E: Covariates along the SE India coast

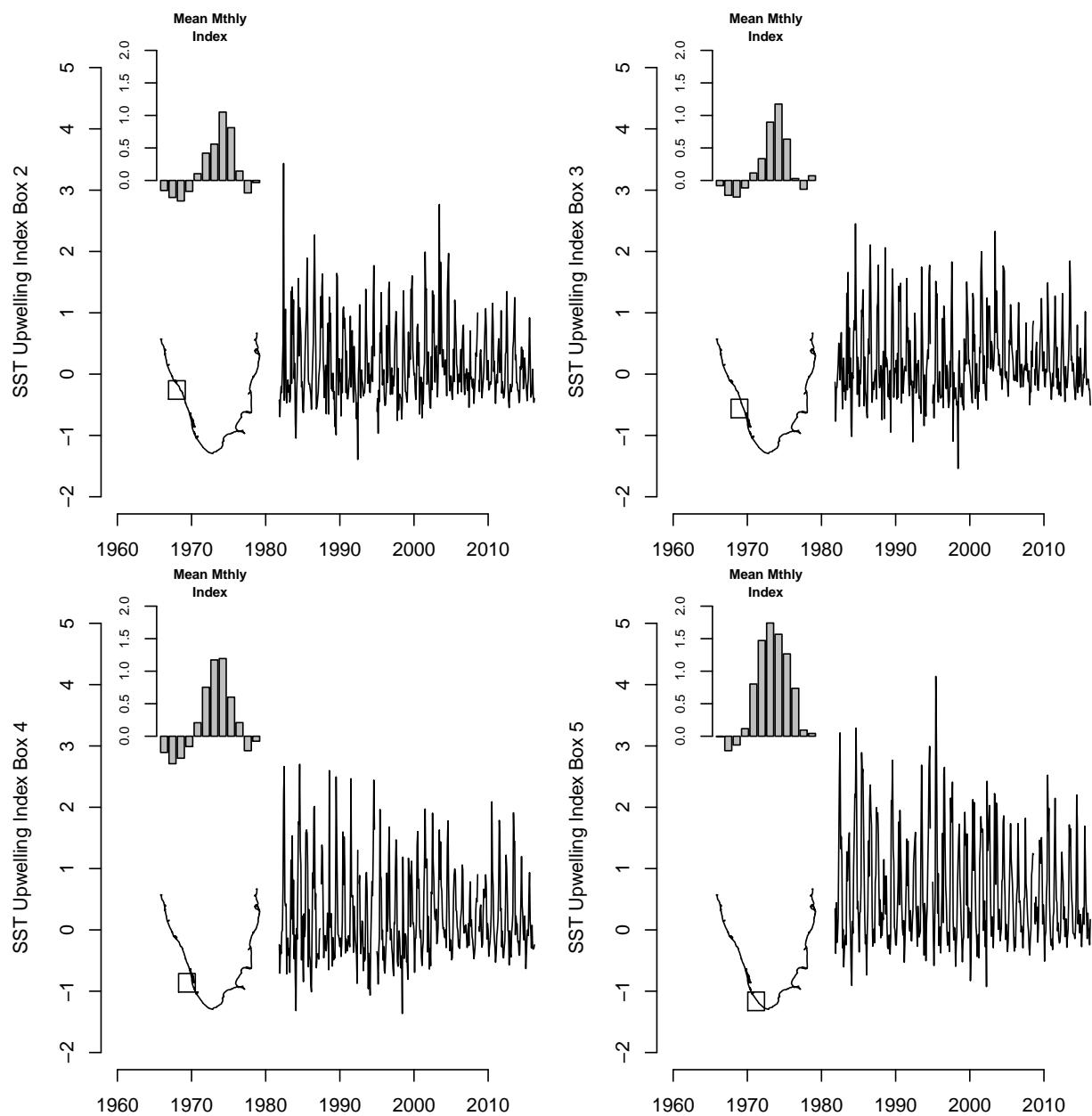


Figure E1. Upwelling index.

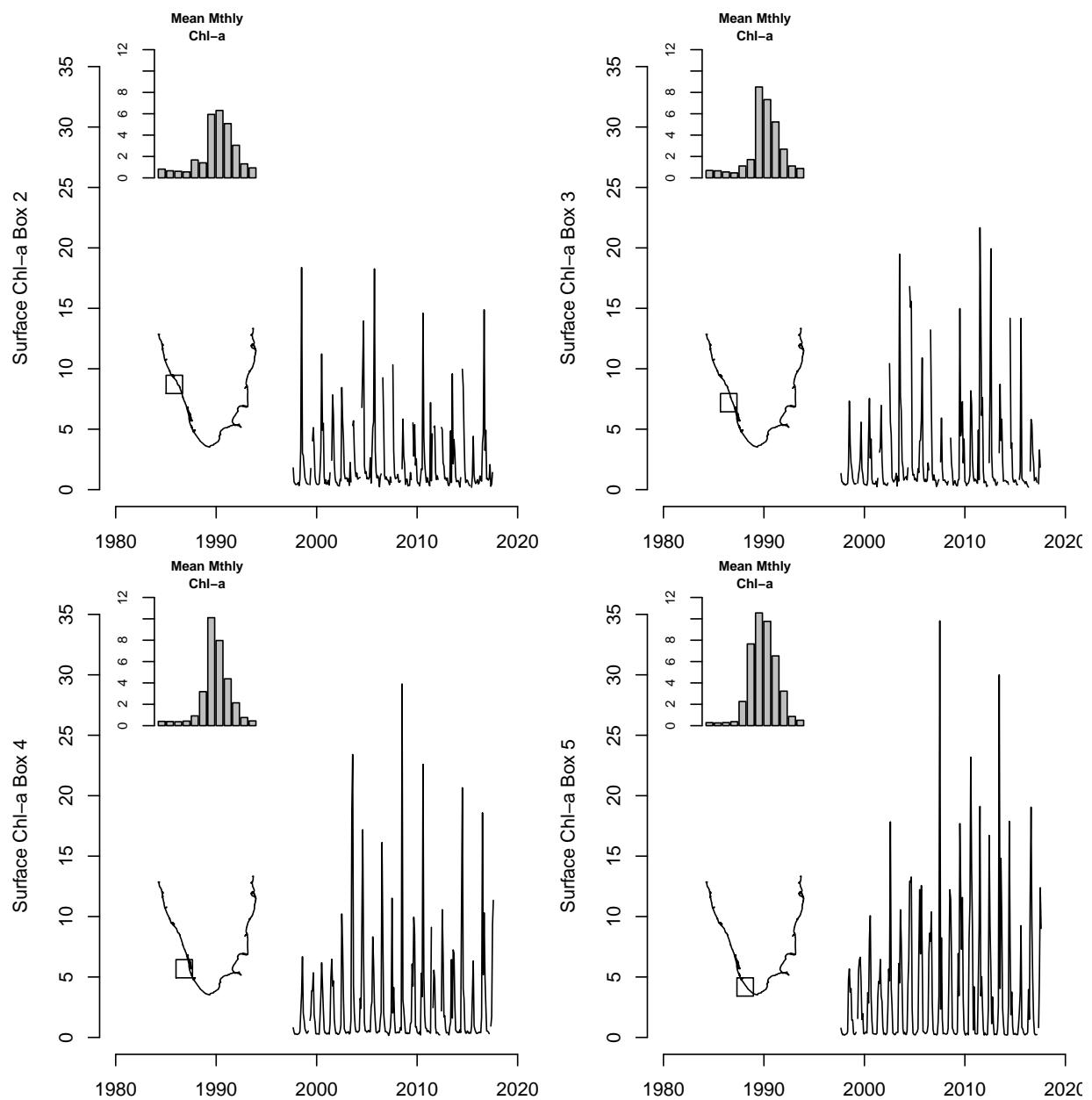


Figure E2. Chlorophyll-a.

Appendix F: Comparison of land and oceanic rainfall measurements

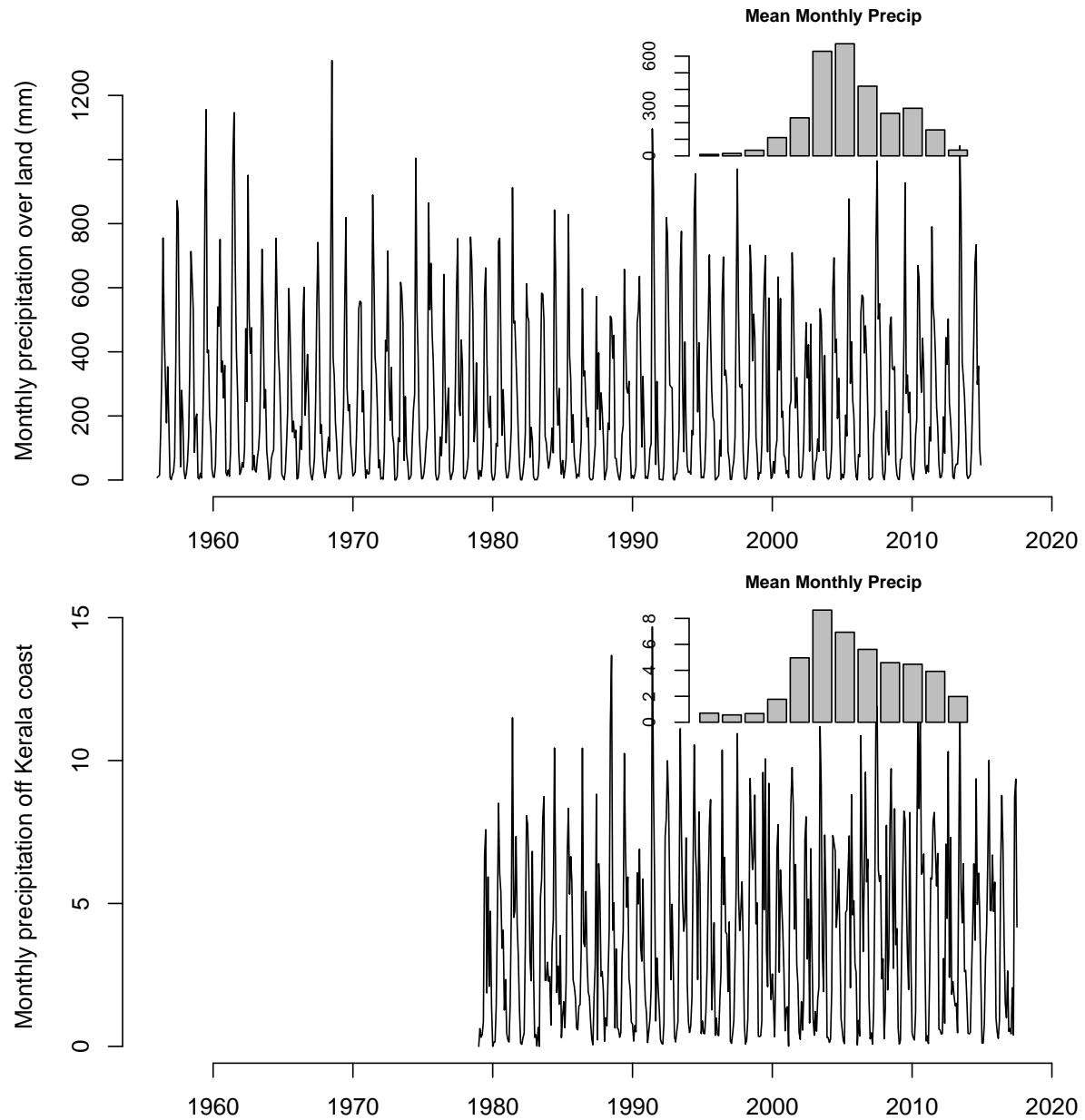


Figure F1

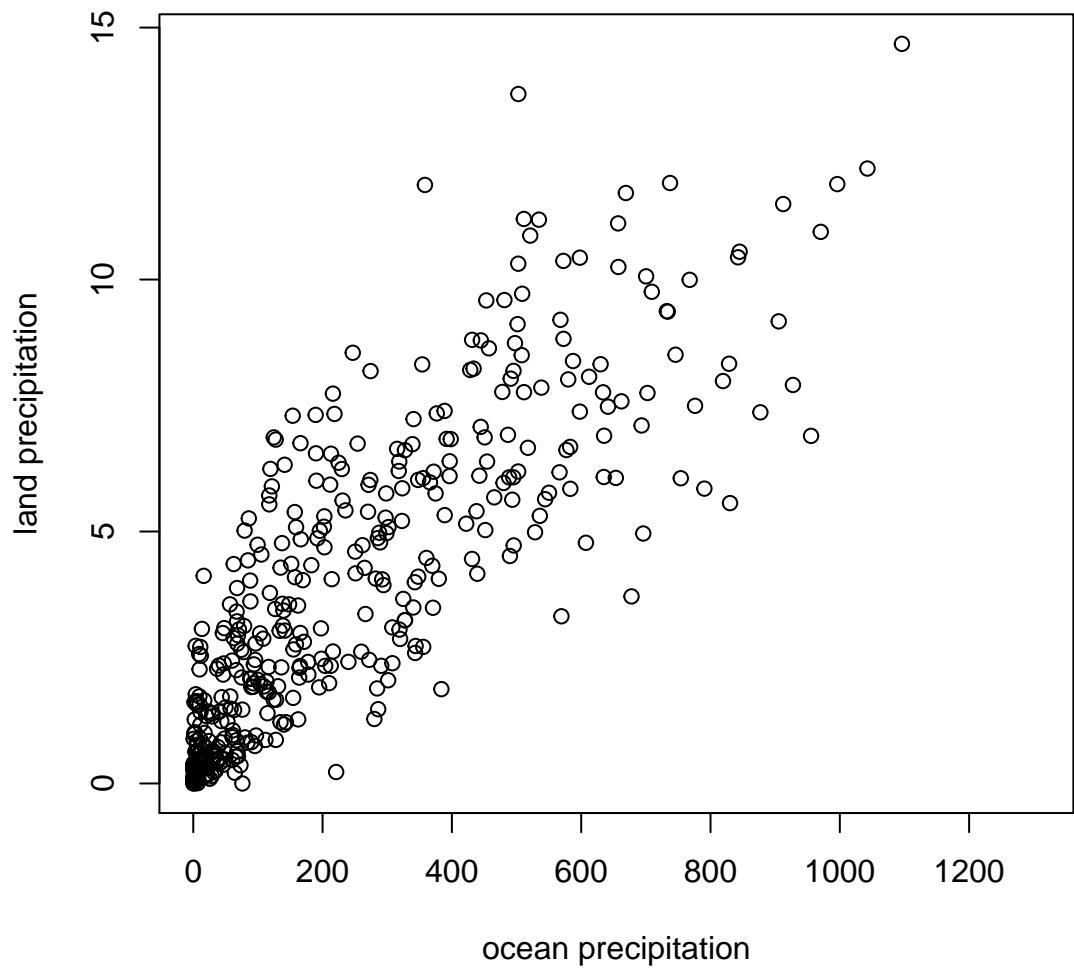


Figure F2. Monthly precipitation measured over land via land gauges versus the precipitation measured via remote sensing over the ocean.

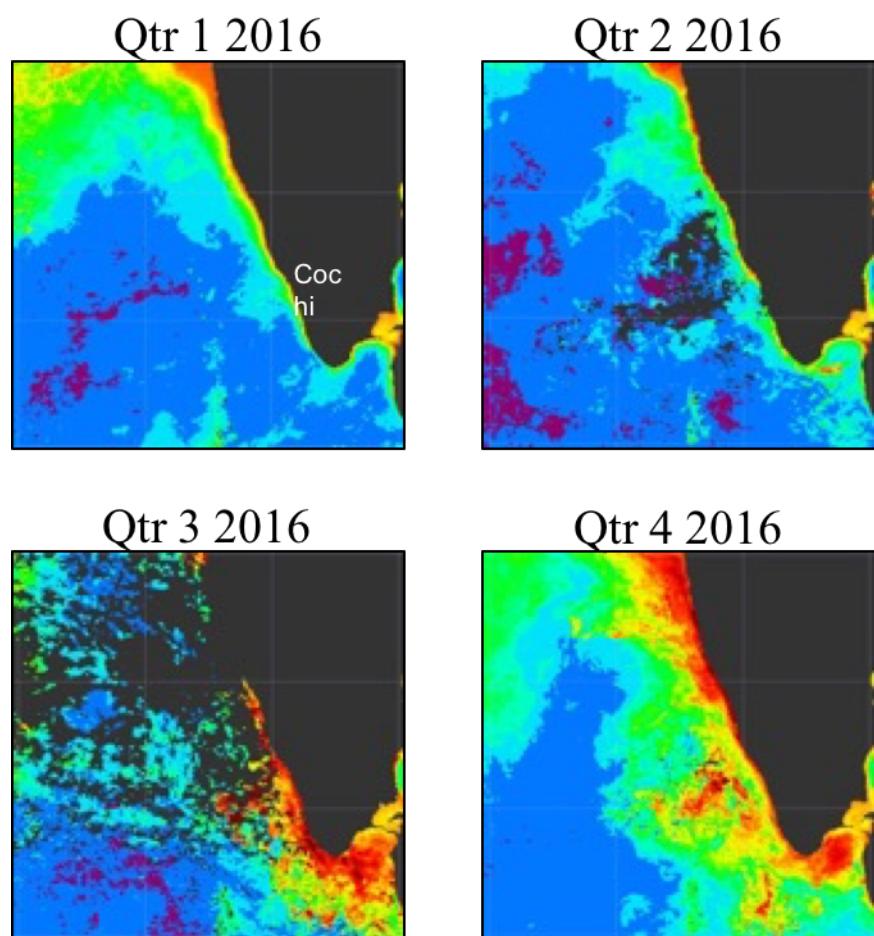


Figure 9

Appendix G: Chlorophyll-a images in 2016

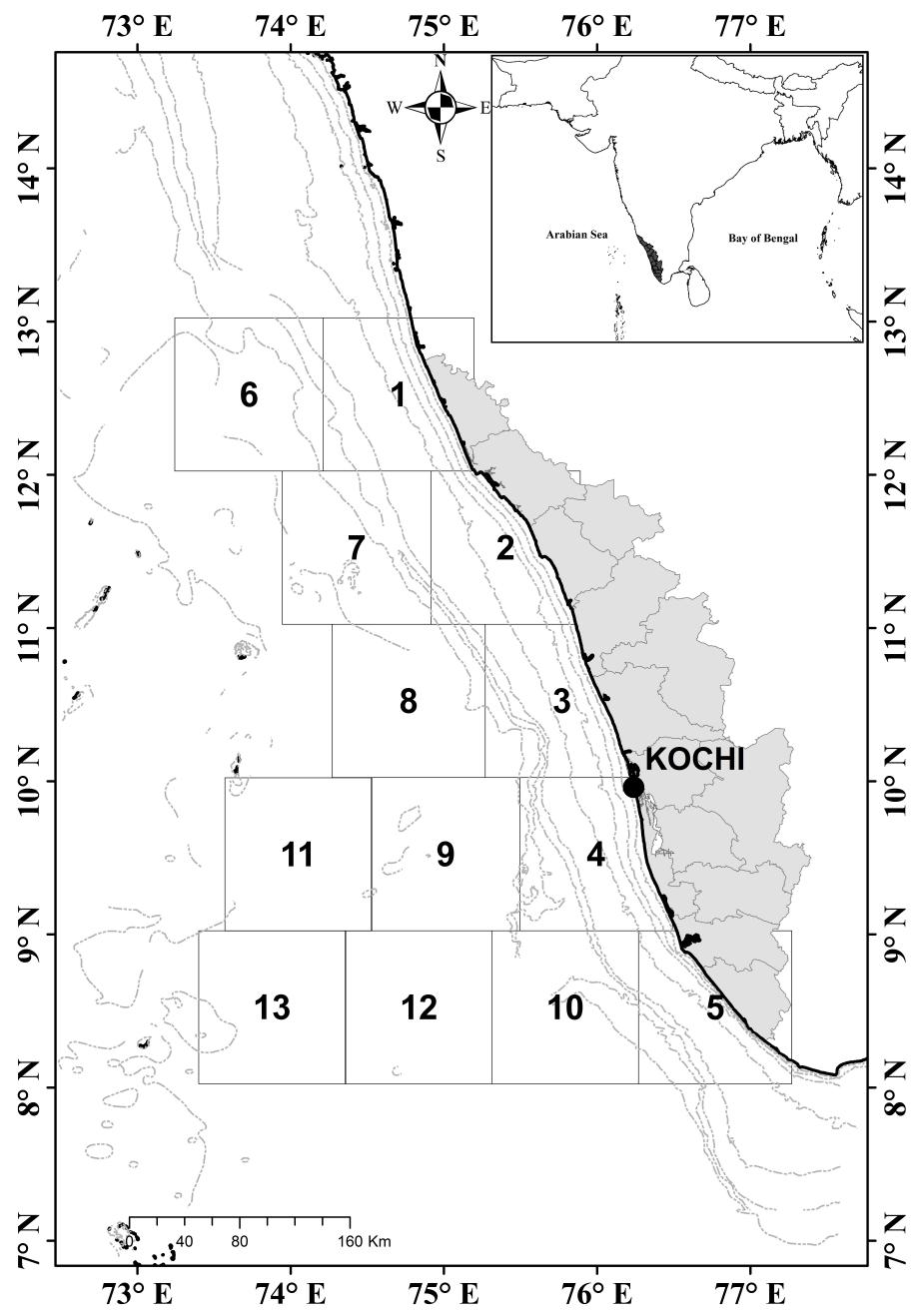


Figure 1

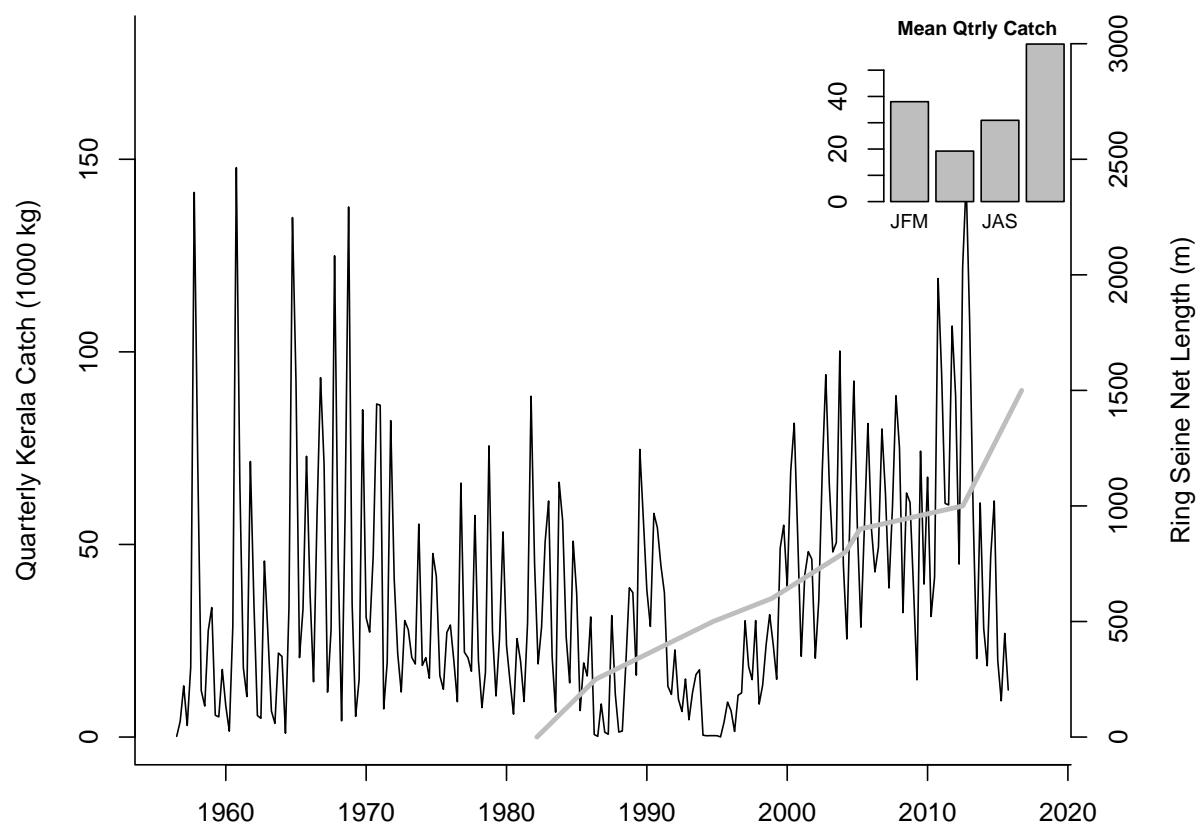


Figure 3

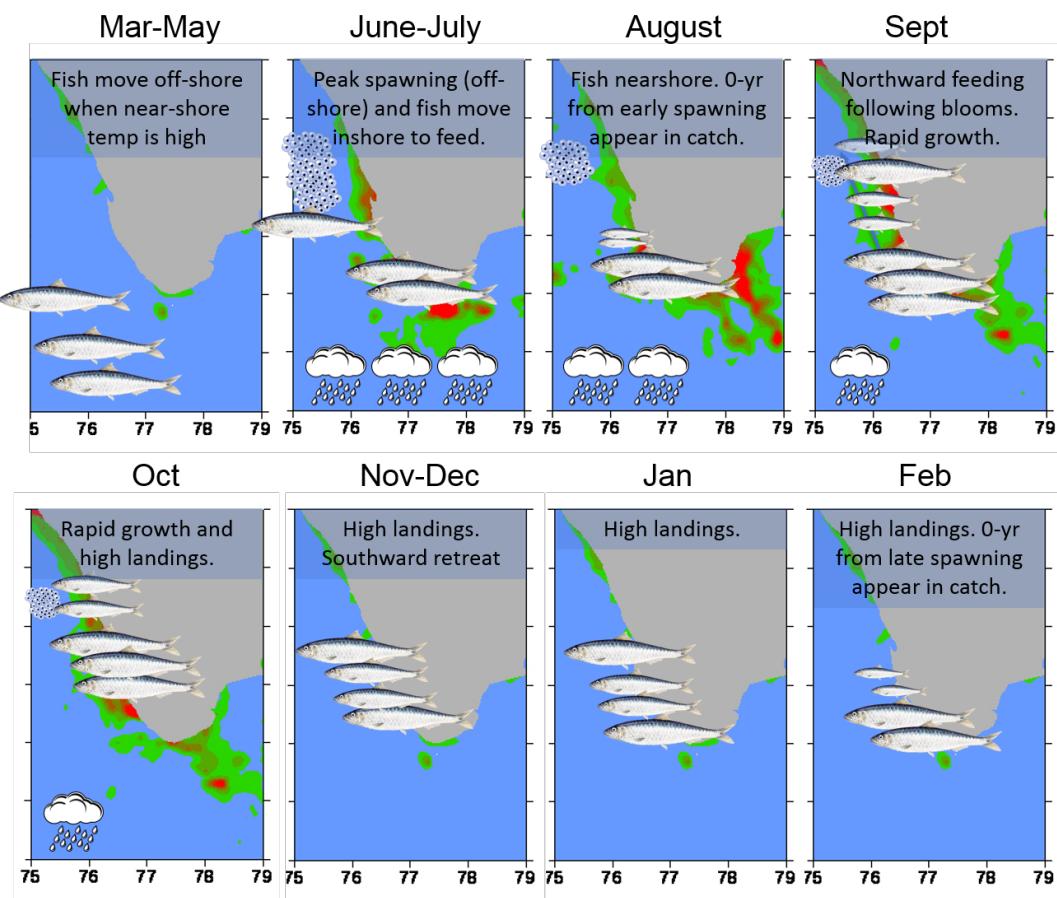


Figure 2

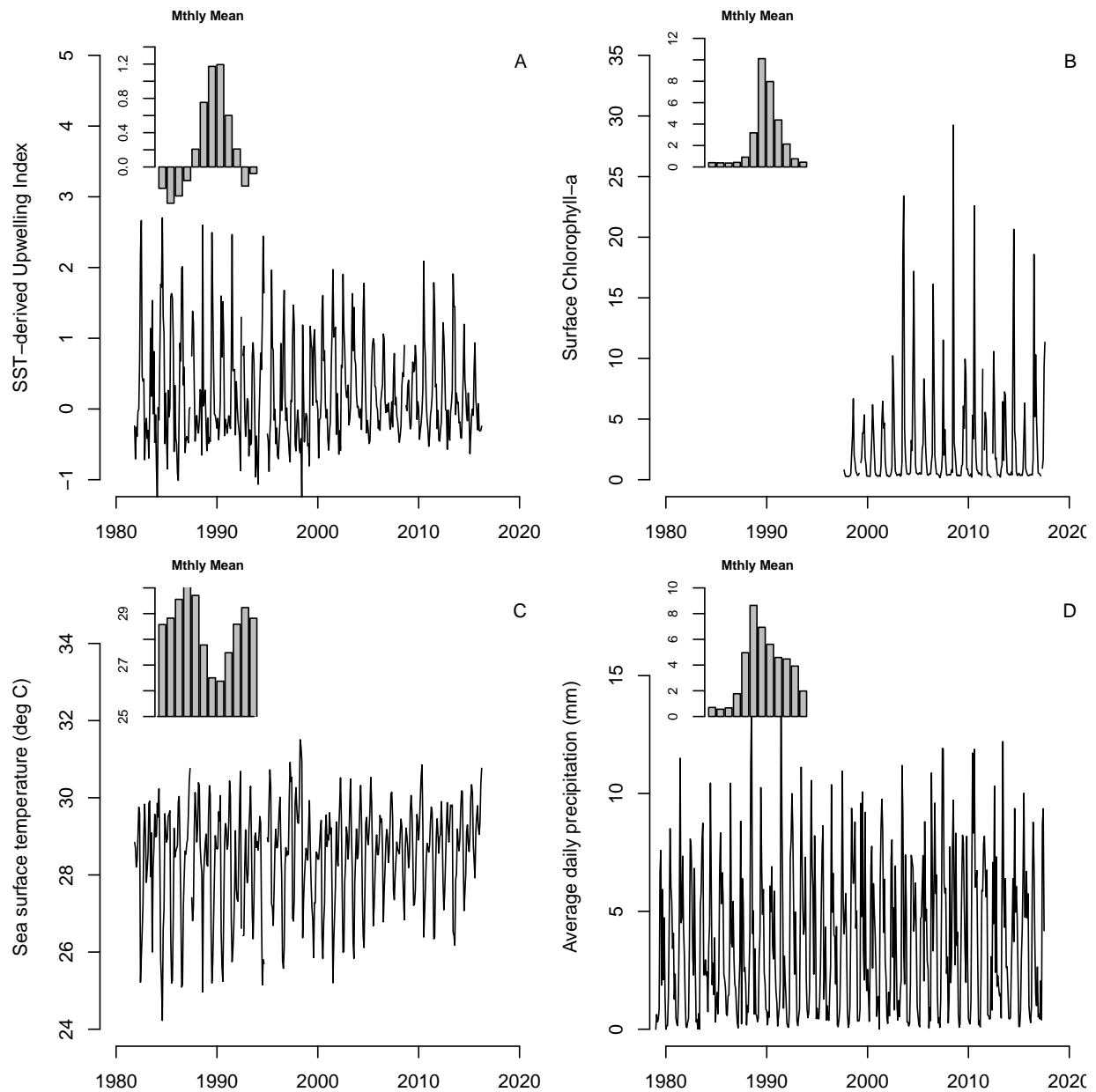


Figure 4

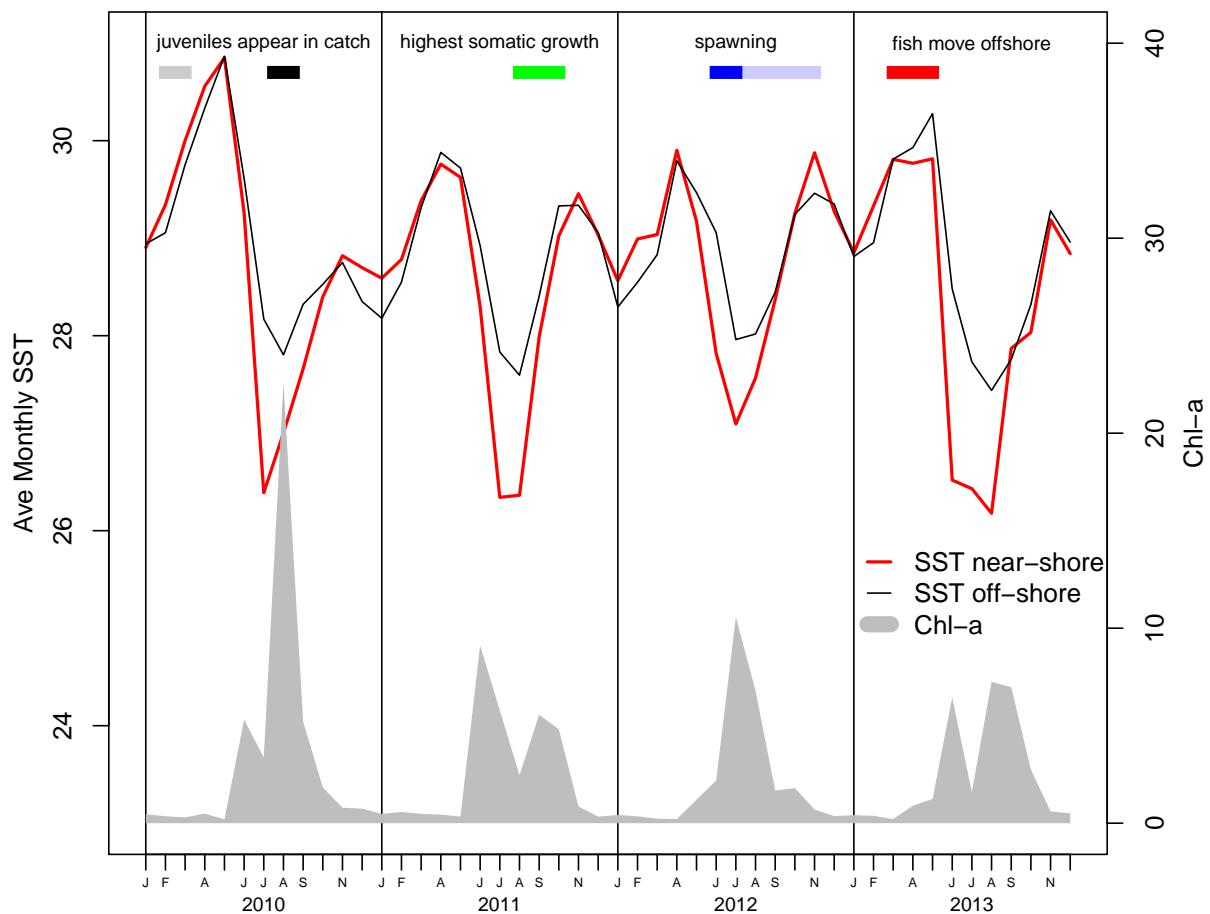


Figure 5

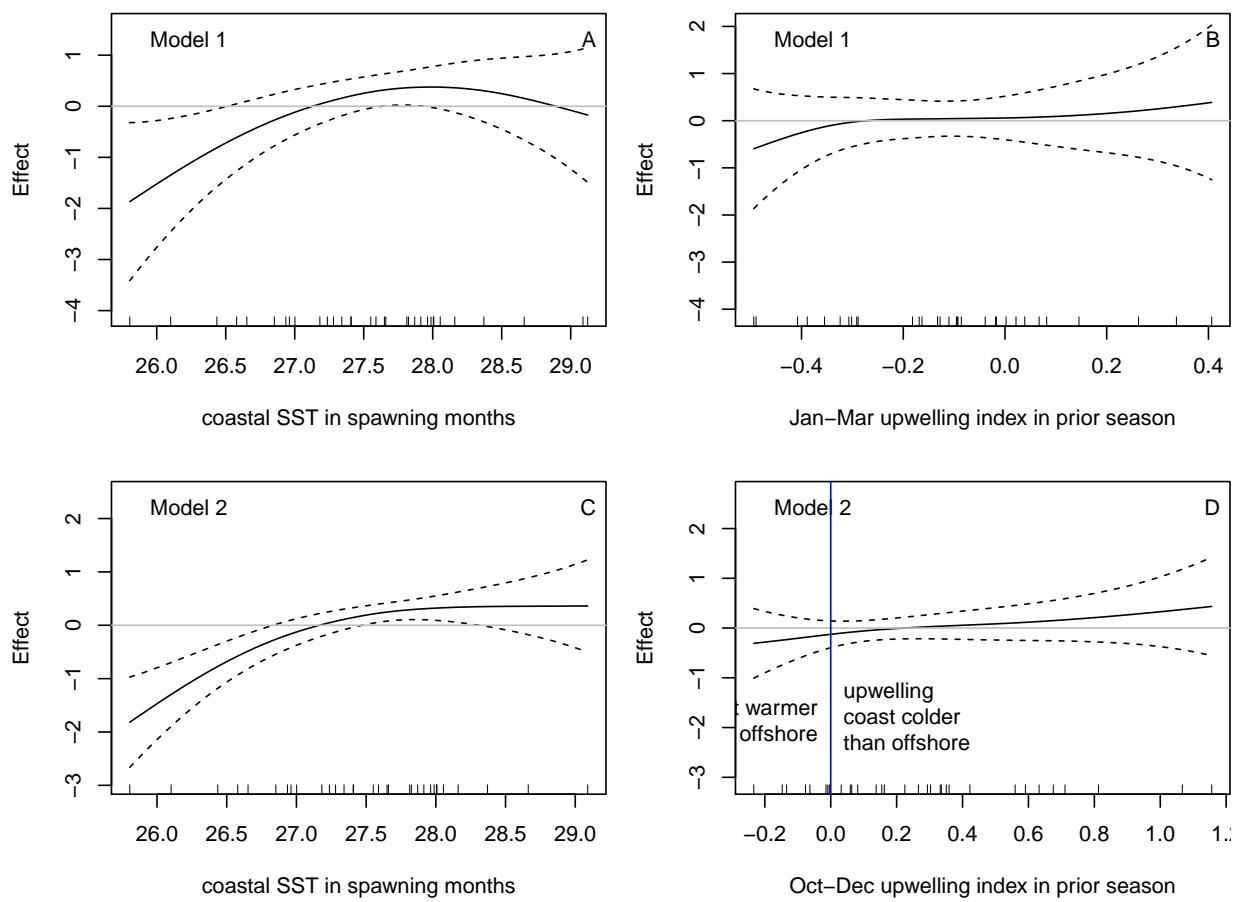


Figure 6

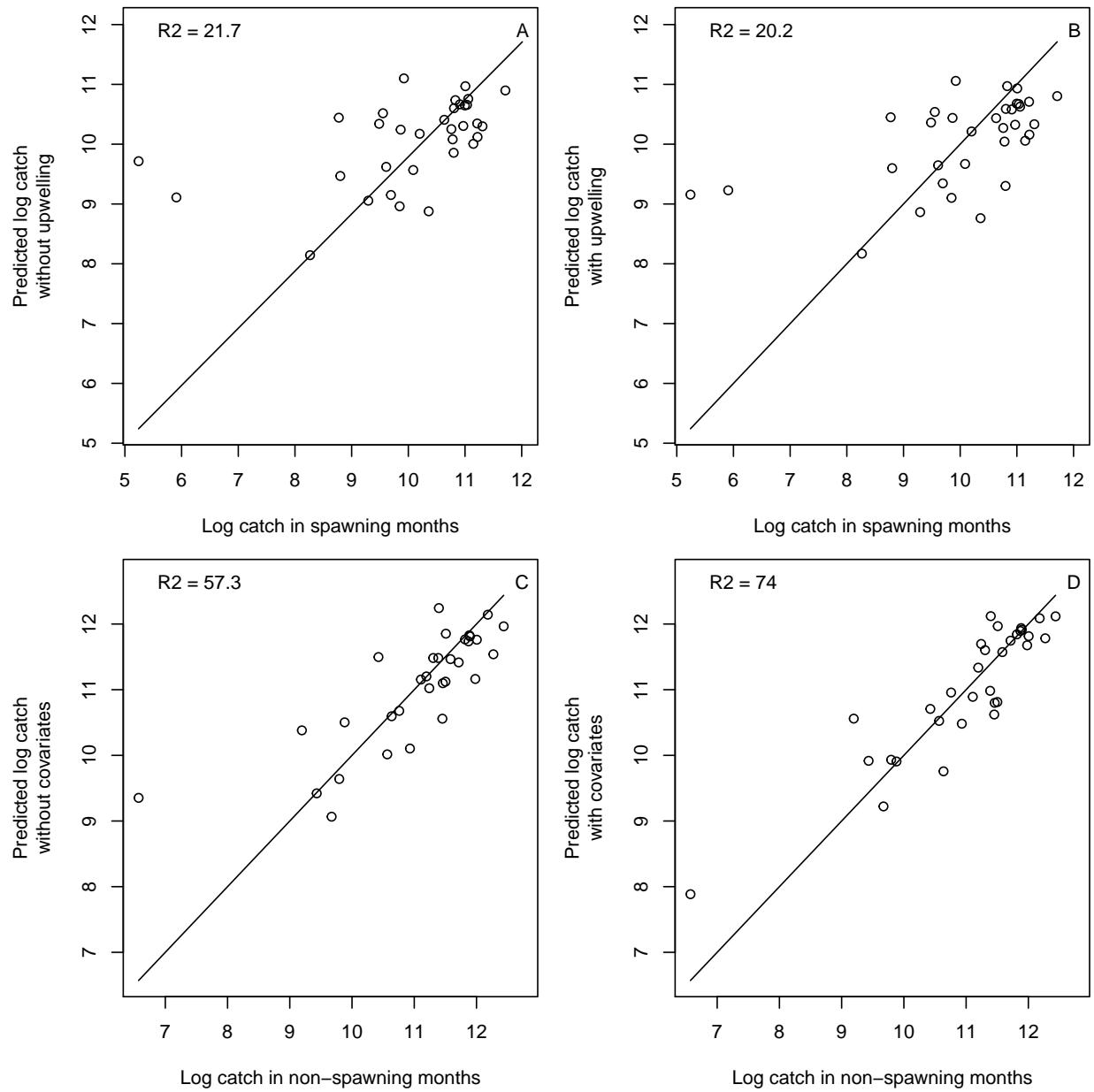


Figure 8