Improving landings forecasts using environmental covariates: a case study on the Indian oil sardine

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MoES-NOAA Collaboration: Development of Predictive Capabilities for Marine Fisheries and Harmful Algal Blooms in Indian Seas

- 2014-2019
- India-USA (NOAA-MoES) Research collaboration
- Improve forecasting:
    - Harmful Algal Blooms
    - **Oil sardine landings**

INCOIS: Indian National Centre for Ocean Information Services

CMLRE: Centre for Marine Living Resources & Ecology

Kochi (Cochin)

Largest city in Kerala state

Hyderabad

Capital of Telangana state

Today’s talk

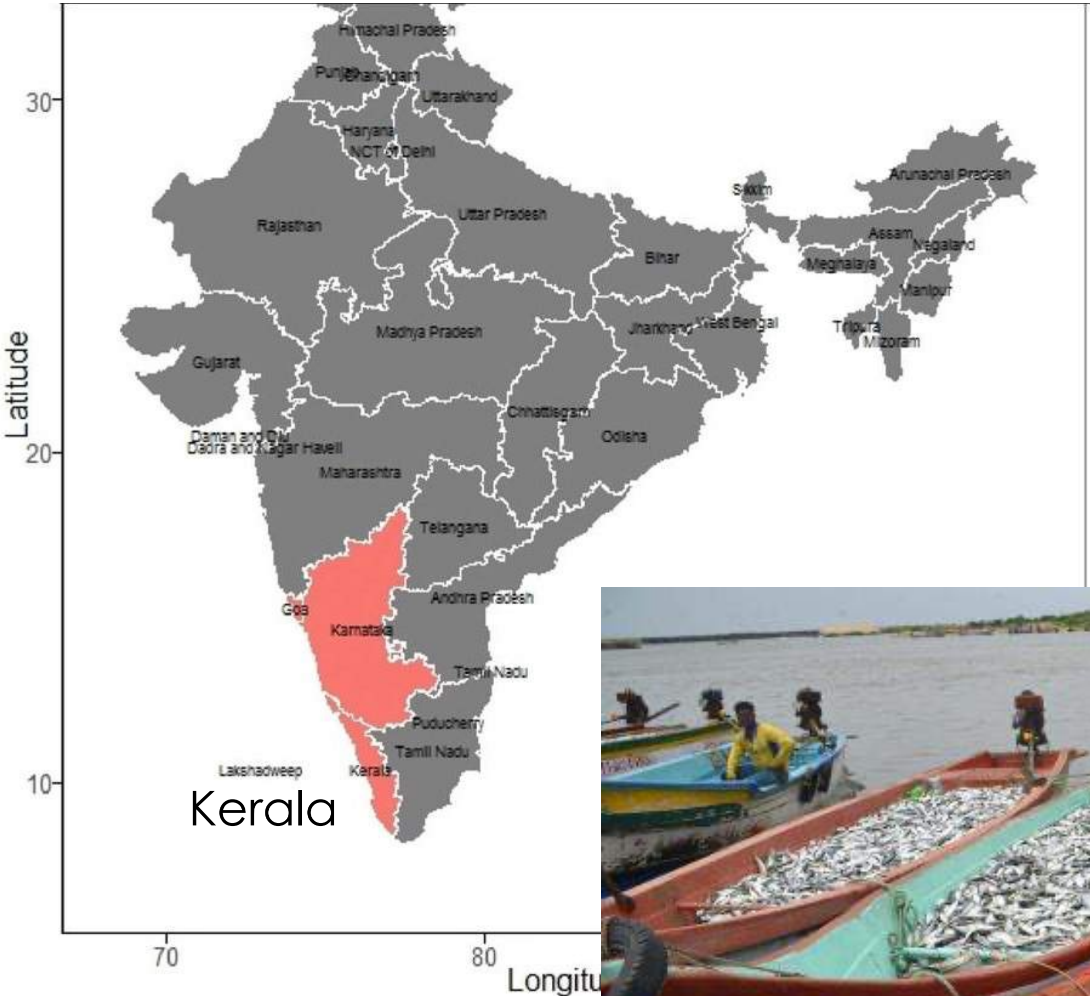
- Fishery --- SE Arabian Sea --- Biology of oil sardines
- Forecasting landings using environmental covariates
- Take home messages about forecasting in general

Kochi harbor

Fishery

Indian Oil Sardine Fishery

ca 20% of the total fish landings in India

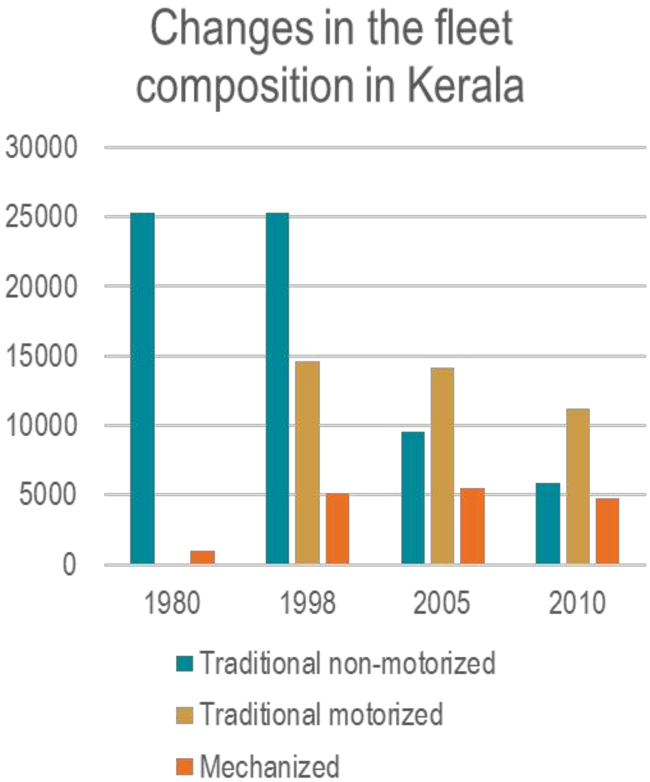


Unregulated coastal fishery with a diversity of fishing vessel types


श्री वराहम

Fleet characteristics have changed over time

Today oil sardines are caught primarily with ring seines using smaller motorized (outboard) boats or larger (inboard) ships



1985-2014 Changes in gear size and power

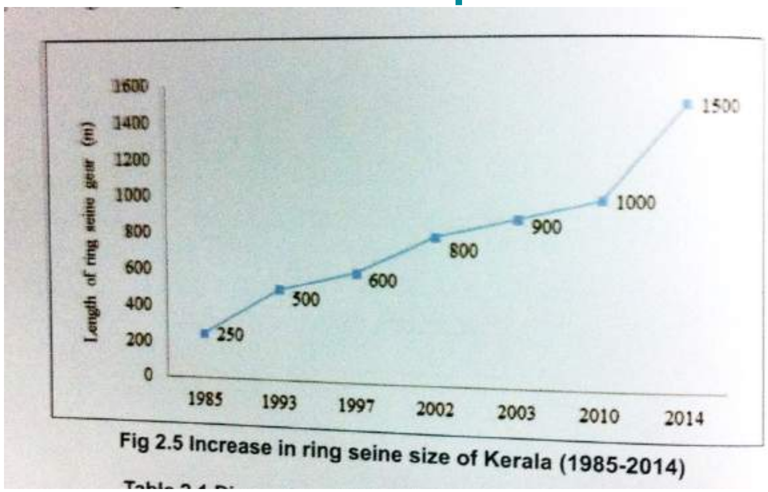
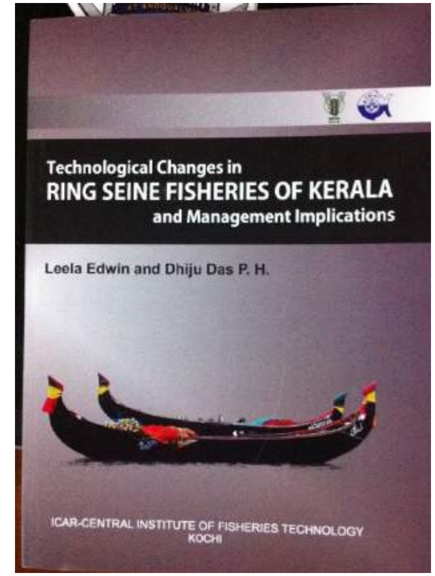


Fig 2.5 Increase in ring seine size of Kerala (1985-2014)

Nets are getting longer



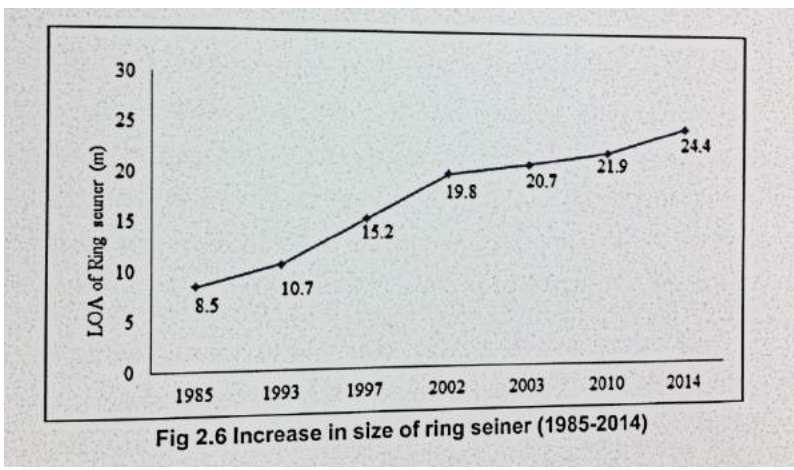


Fig 2.6 Increase in size of ring seiner (1985-2014)

Boats are getting longer

Engines are getting stronger

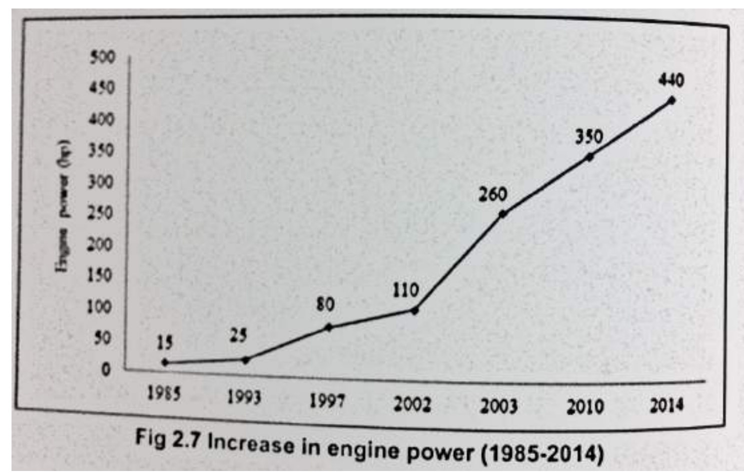


Fig 2.7 Increase in engine power (1985-2014)

- Spatially distributed
- Restricted to nearshore
- Non- or low-refridgeration
- Lower engine power
- Not able to target fish like a highly-mechanized fleet



Landing centers are distributed along the coast. The fishing surveys occur here.

Small landing center in north part of Kochi


T.S.DEVASHREE
GOODS CARRIER
DAY NIGHT EXPRESS
LEYLAND
TN.49.BY.3388
GOOD'S
KALAI
CARRIER
KALAI TRADERS
ALL INDIA


EAC

Oil sardine landings

Catch data are collected by Central Marine Fisheries Research Institute (Kochi). Data on the catch by species is collected at 187 landing centers in Kerala (and over 1511 along the entire coast).

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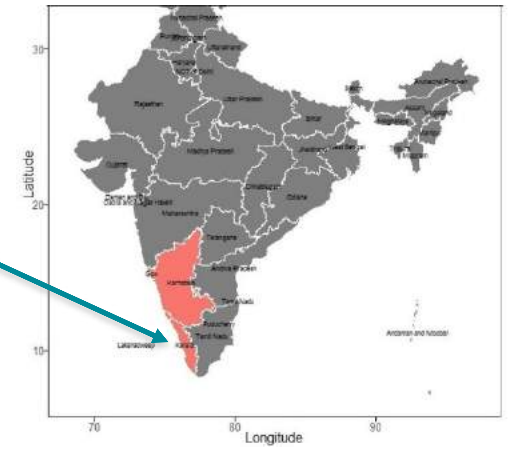
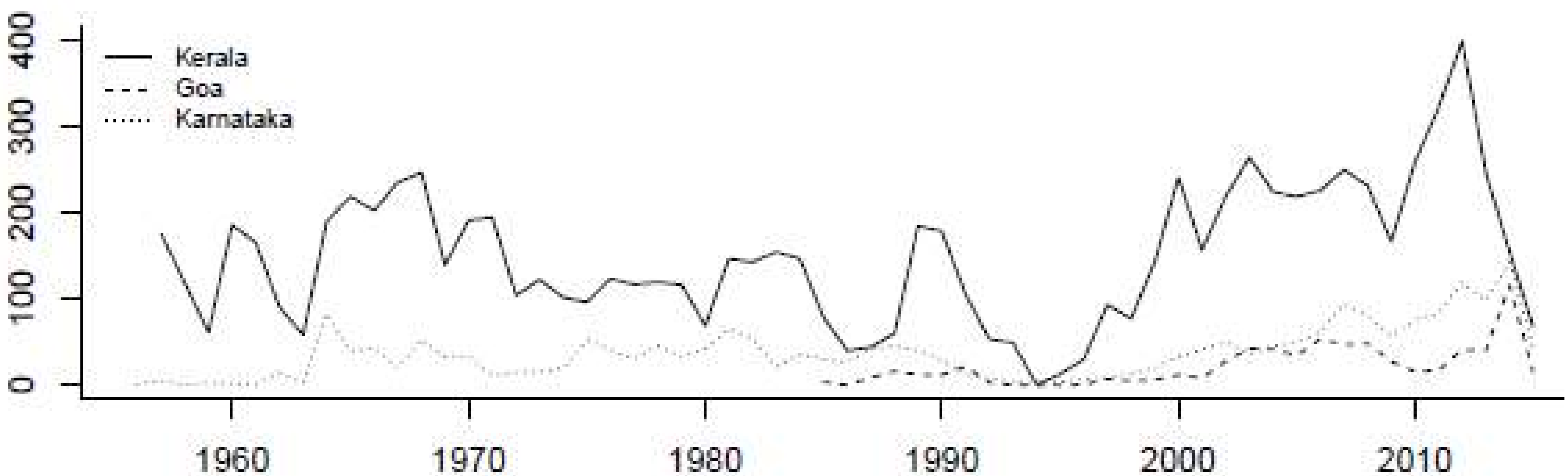
These pictures from http://www.steyn.pro/kerala/ from a study of cell phone use by fishers

Yearly trends in the SW coast oil sardine catch

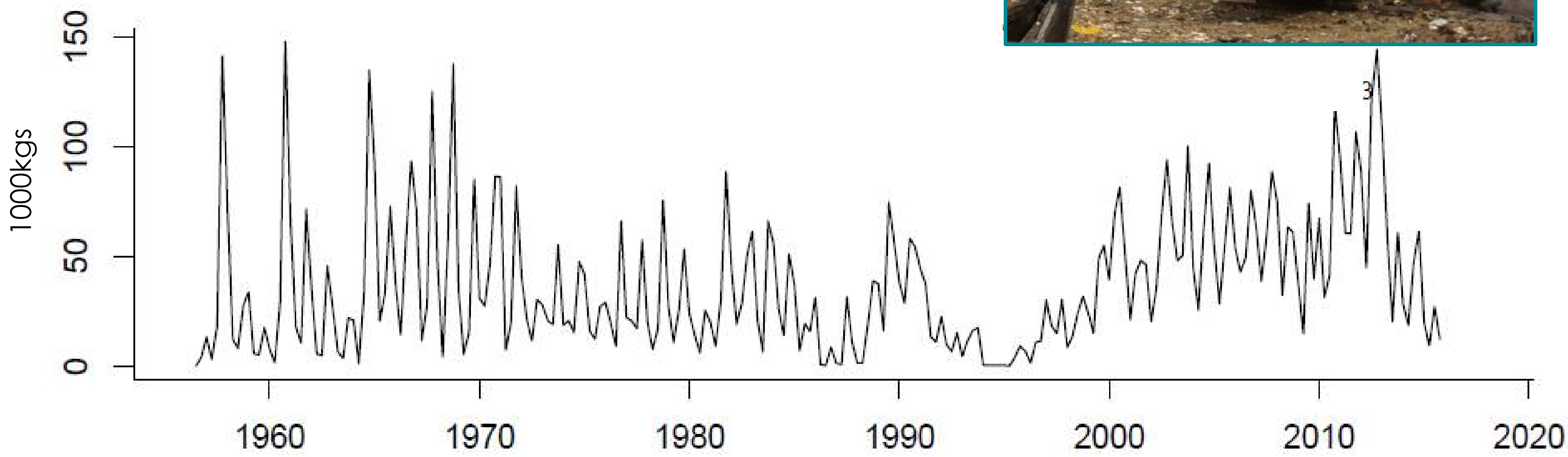
Kerala catch makes up the majority of the SW coast landings





High variability in the catches

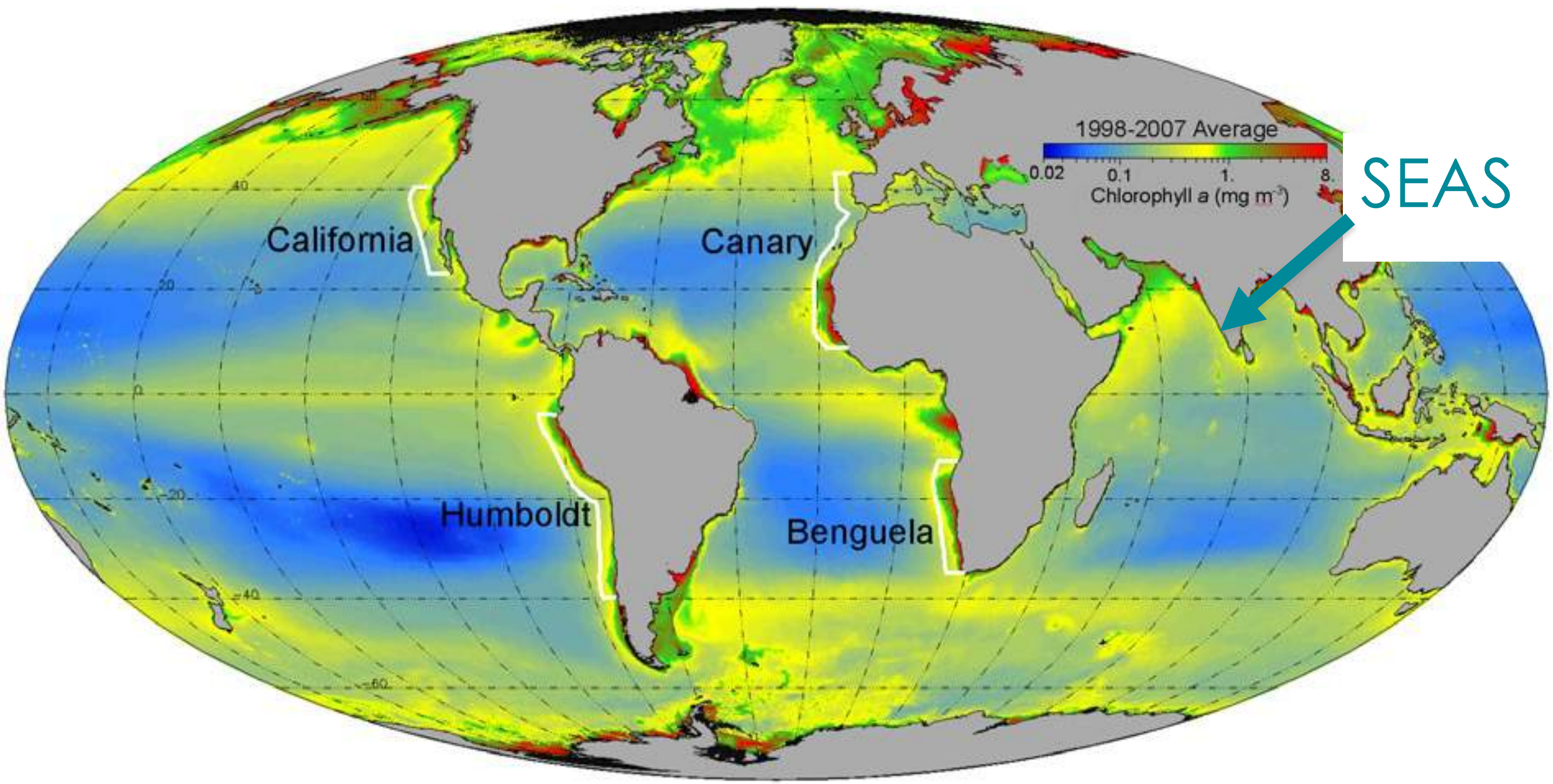
- seasonal
- **yearly**



Quarterly Kerala oil sardine landings

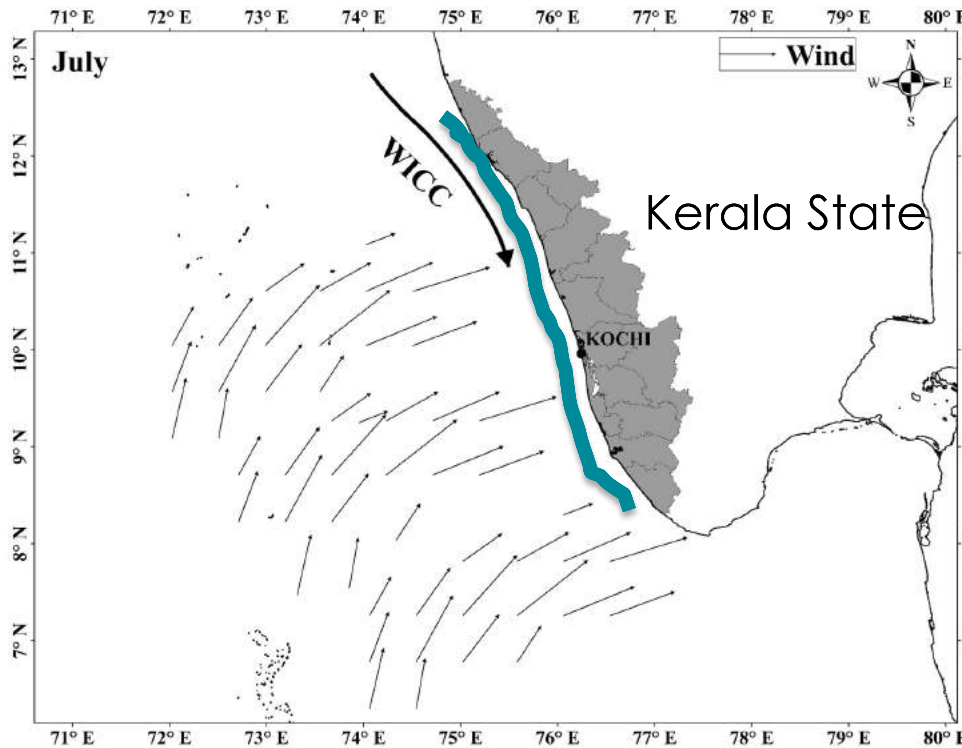
SE Arabian Sea

The SE Arabian Sea is one of world's major seasonal upwelling zones driven by monsoon winds

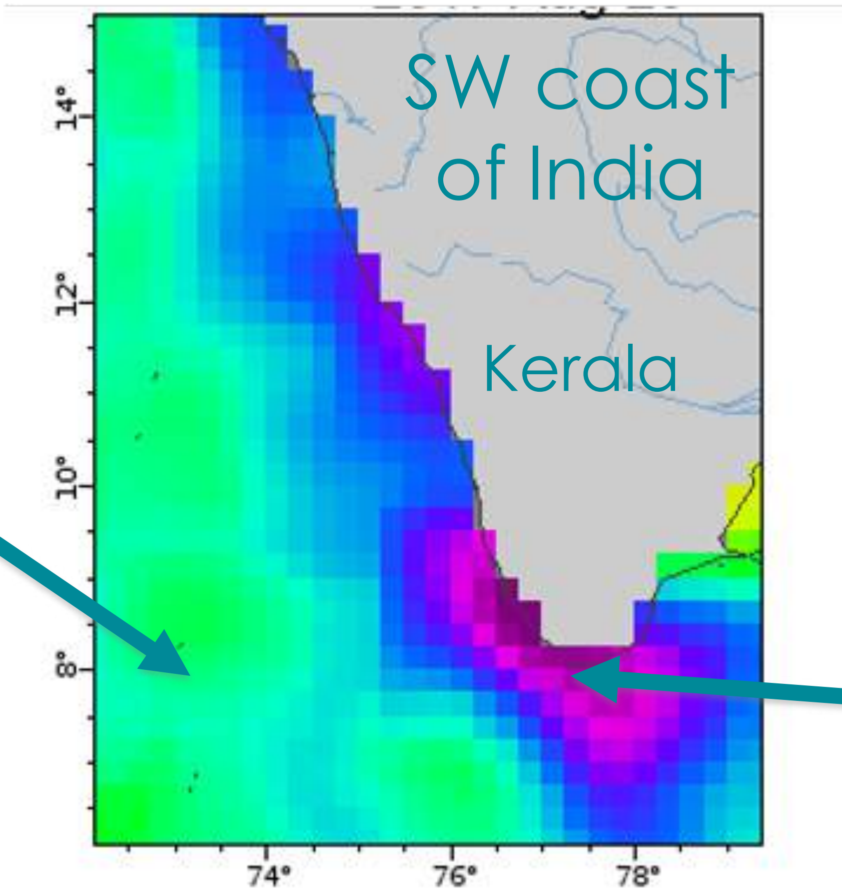


Surface Chl-a 1998-2007 Average

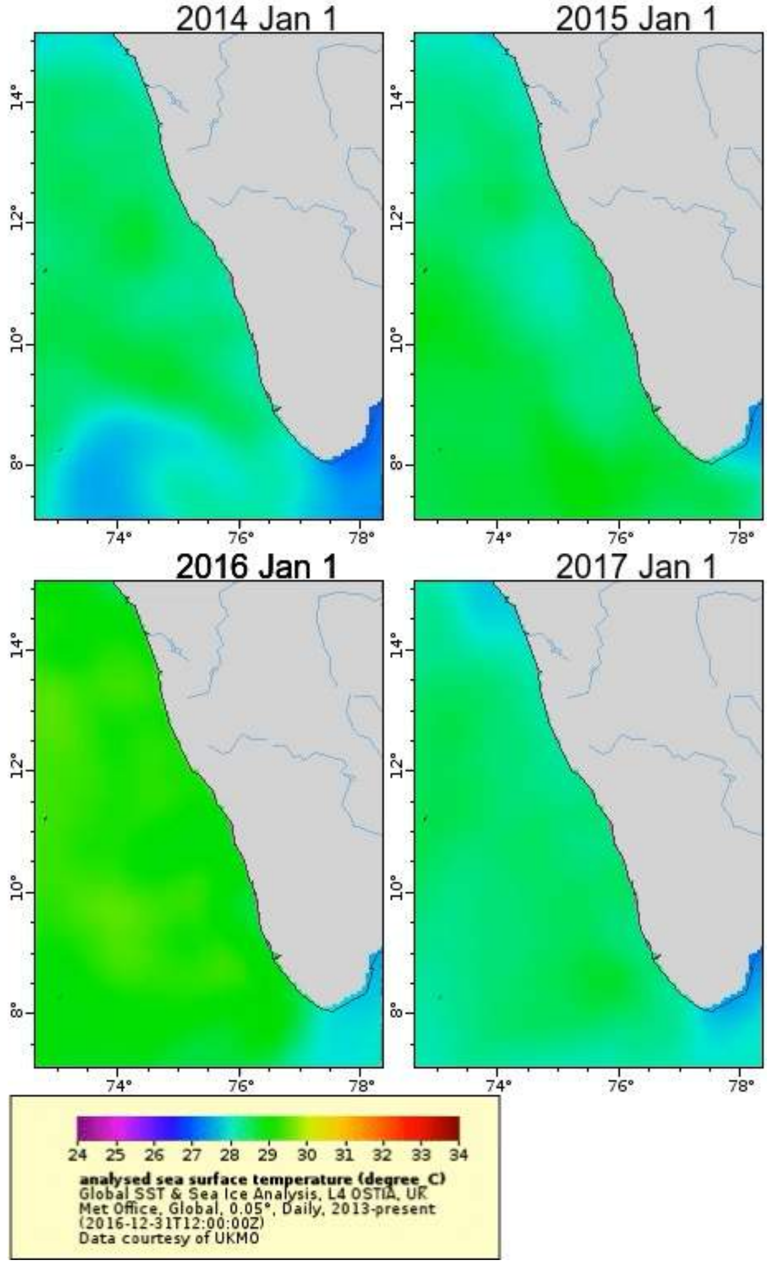
June to September



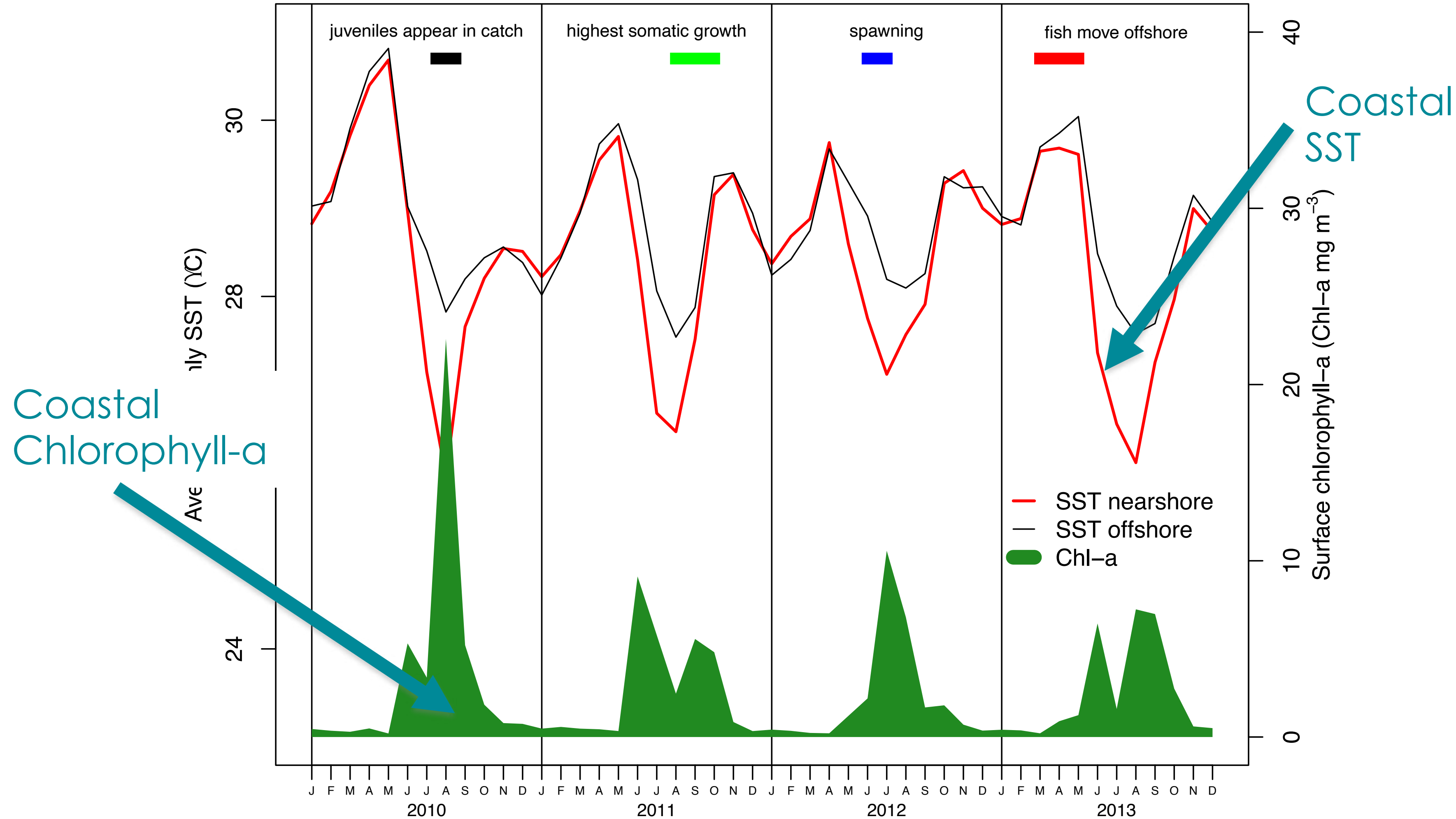
Sea surface temperature signature of upwelling (Sept 1)



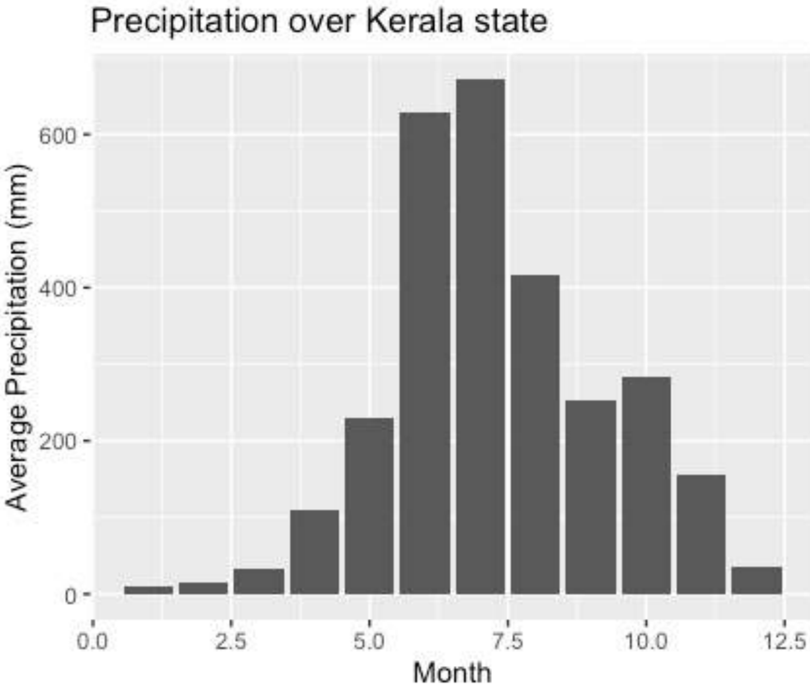
Sea surface temperature as it changes through the year



Seasonal cycle of the environment

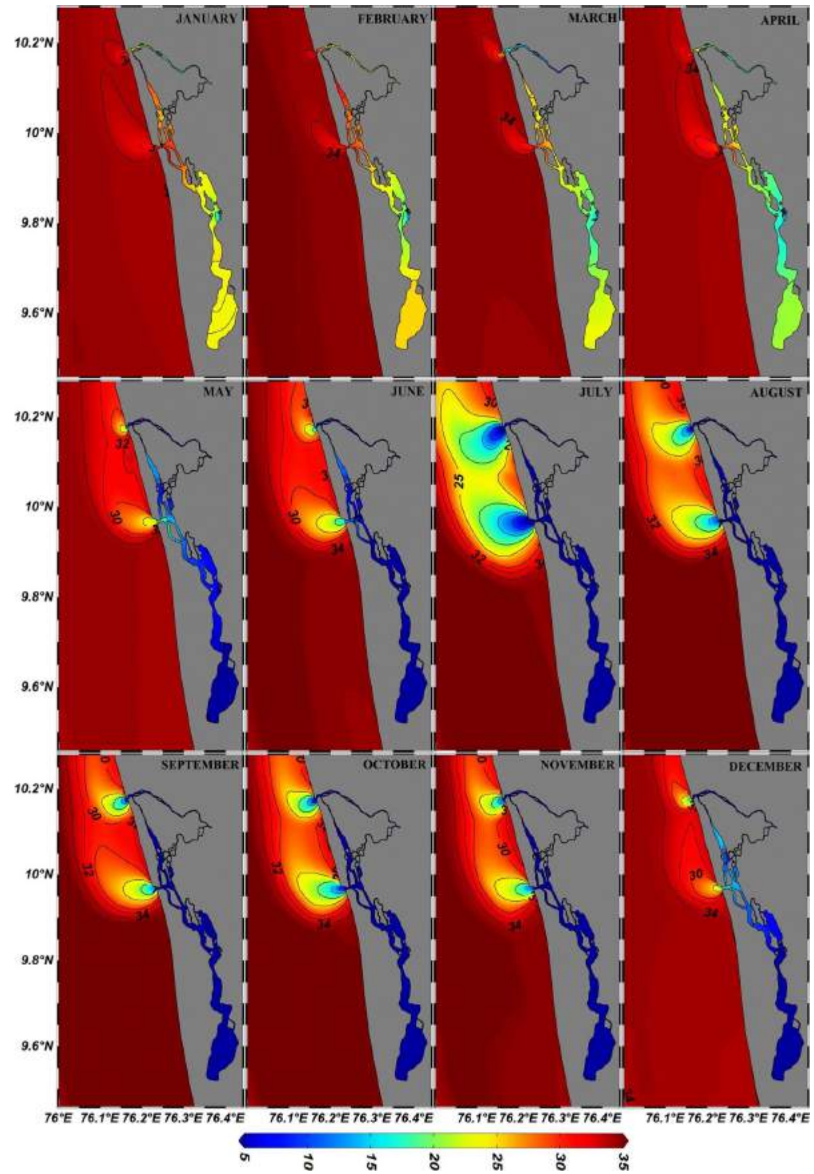


There are 44 rivers in Kerala which flow into SE Arabian sea



Seasonal cycle of river plumes: low salinity + nutrients

Seena, G., Muraleedharan, K.R., Revichandran, C. *et al.* Seasonal spreading and transport of buoyant plumes in the shelf off Kochi, South west coast of India- A modeling approach. *Sci Rep* **9,** 19956 (2019)

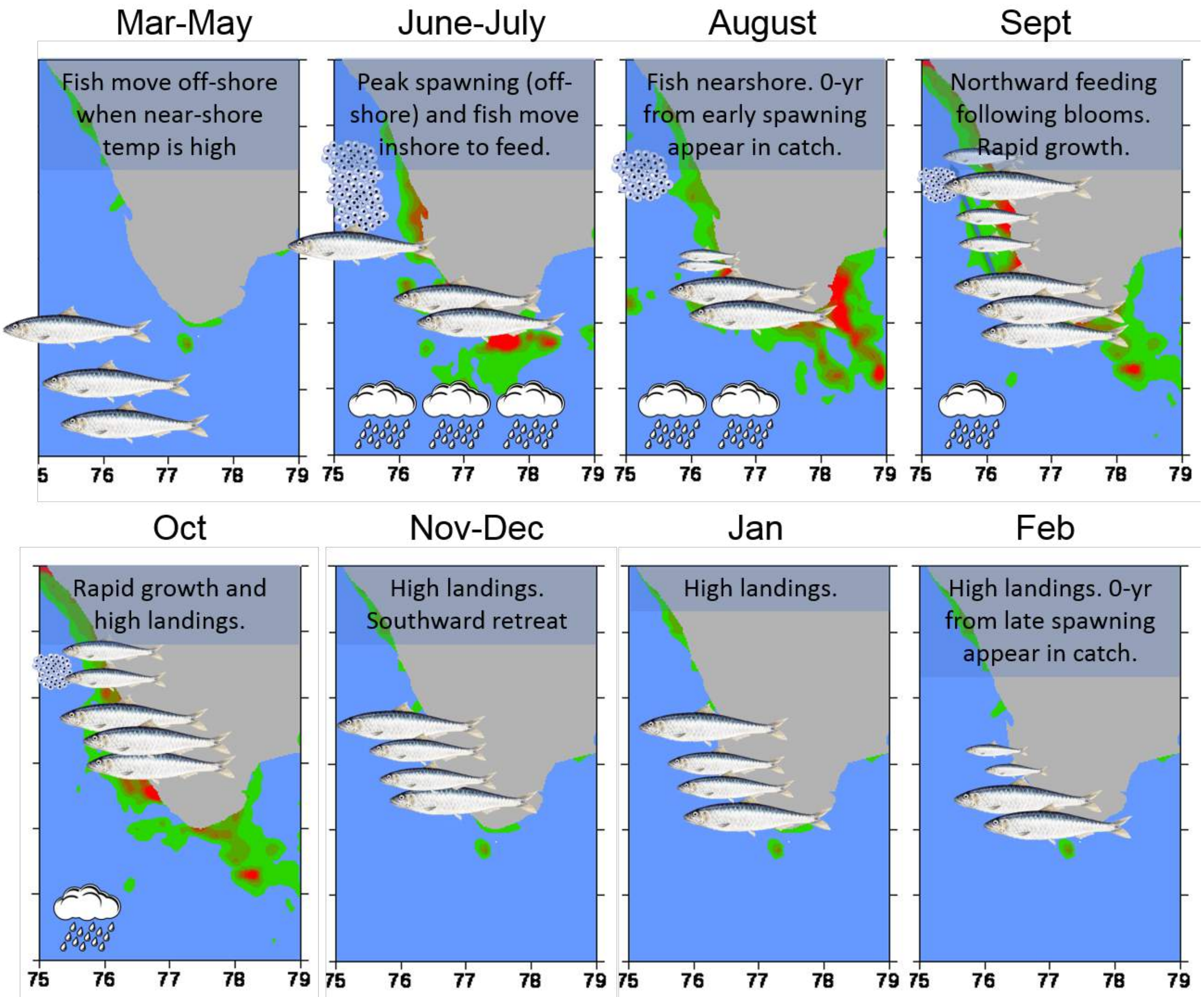


Oil sardine life history

Spawn in June-July

Mature at age 1 (12 months)

2 to 2.5 yr life span



Forecasting landings

Big drops in oil sardine catch have cascading impacts on economy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Marine fish catch drops 5.3% in 2015, 51% decline in oil sardine landings

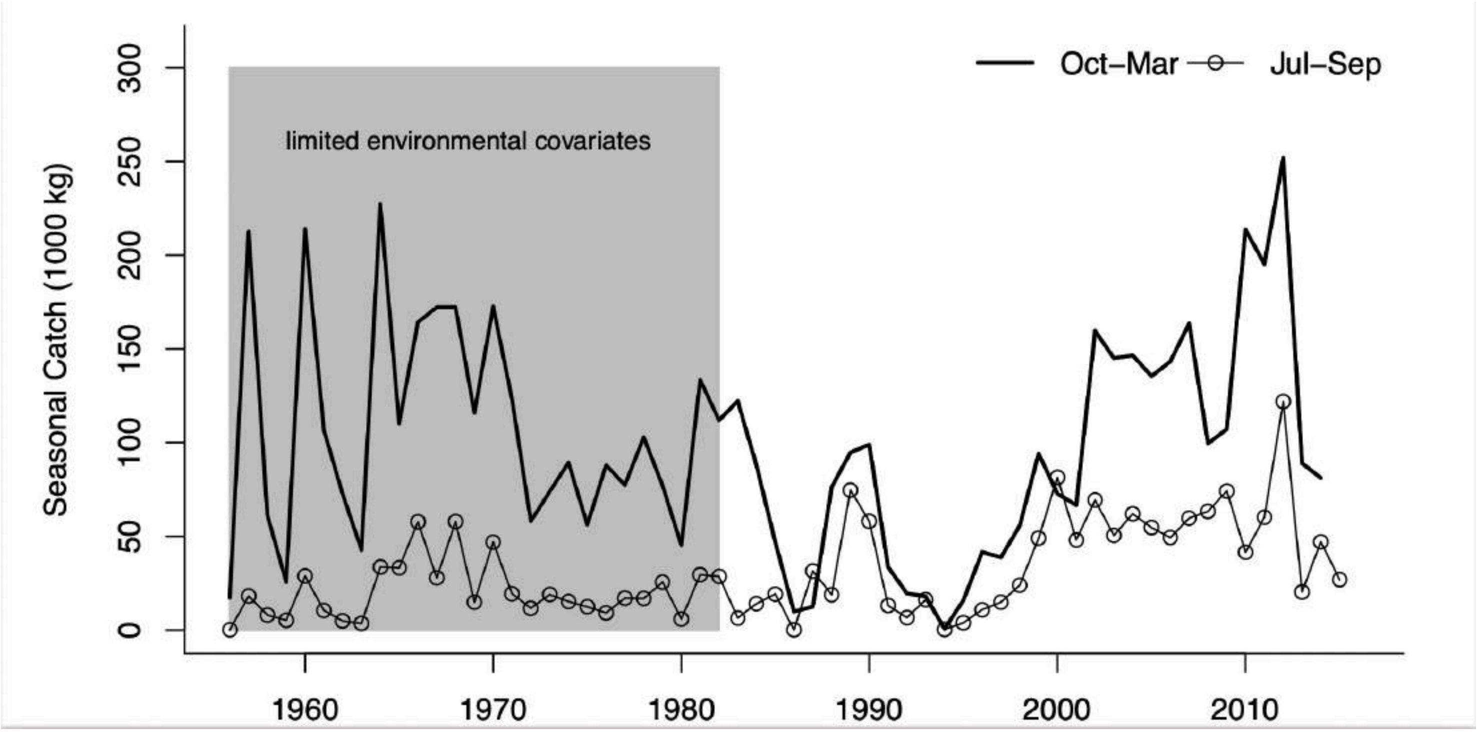
V. SAJEEV KUMAR

Strategy

Examine hypotheses concerning how environmental events affect catch

- Juvenile survival
- Somatic growth (time to reach maturity)
- Exposure to the fishery (feeding close to shore)

Do these effects translate to better catch forecasts?



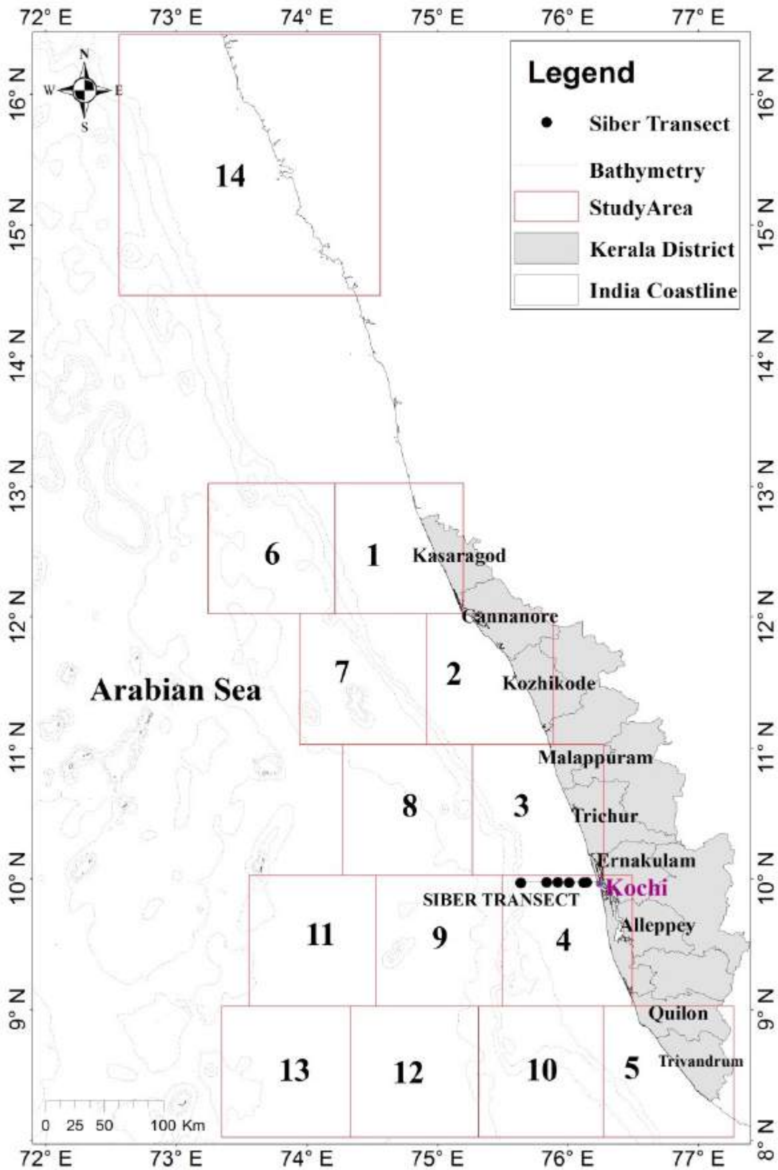
Environmental covariates

Remote-sensing data (mostly)

From 1984 at least
- sea surface temperature
- winds
- precipitation over ocean
- precipitation over land
- ocean climate indices

Not enough data
- Sea surface height
- Salinity
- Chlorophyll-a

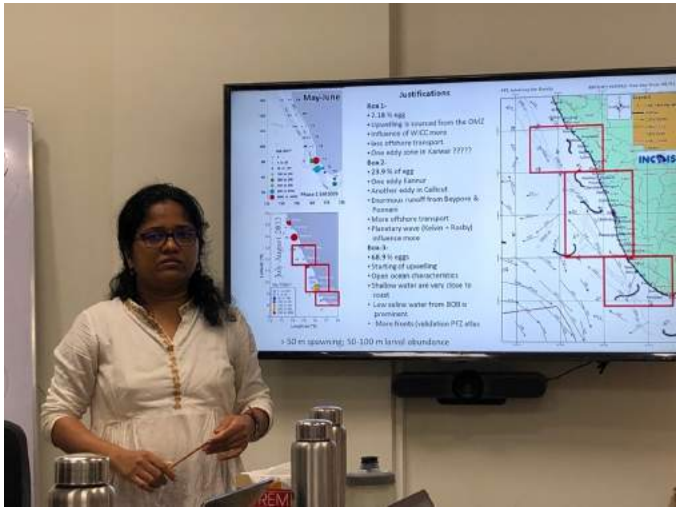
Too noisy
- tide level



What covariates should we test? A 4-year discussion with with Indian and US oceanographers and fisheries biologists (+ reading 100 years of research)

TABLE 1 Covariate models for the July–September (S_t) and October–March (W_t) landings. In the model (left) column, the first line is the environmental covariate. The response variable and the mechanism by which the covariate is postulated to affect catch is shown below the covariate (see Notes for the codes). The tests did not impose a direction (positive or negative) and some environmental covariates have been hypothesized to have both positive and negative impacts on oil sardines.

Model	Description and justification
Jun–Jul and Apr-Mar ocean precipitation AF: S_t	Precipitation over the ocean may directly or indirectly prompt spawning, after which spent adults migrate inshore and are exposed to the nearshore fishery.
Jun–Jul land precipitation AF: S_t GS: W_t, W_{t+1}, S_{t+1}	Summer monsoon precipitation over land leads to high nutrient input from river discharge. At high levels, this leads to eutrophication and anoxia, which drives adults off-shore away from the fishery. At moderate levels, this supports nearshore productivity.
Apr–Mar ocean precipitation SS: W_t, W_{t+1}, S_{t+1}	Spring precipitation is an indicator of climatic conditions during egg development, which affect spawning success and thus the cohort strength.
Jun–Sep upwelling AF: S_t GS+AF: W_t GS: W_t, W_{t+1}, S_{t+1}	Upwelling drives phytoplankton blooms which bring fish closer to the coast (and the fishery) and which promote larval and juvenile growth and survival. However extreme upwelling advects phytoplankton biomass offshore and brings hypoxic water to the surface.
Mar–May r-SST AF: S_t SS: W_t, W_{t+1}, S_{t+1}	Extreme pre-monsoon heating events drive mature fish from spawning areas, resulting in poor recruitment and fewer 0-year fish.
Oct–Dec ns-SST GS: W_t, W_{t+1}, S_{t+1}	October-December are the peak somatic growth months, and larval and juvenile growth and survival are affected by temperature in the nearshore feeding area.
Jul-Sep and Oct-Dec CHL AF: S_t GS+AF: W_t GS: W_{t+1}, S_{t+1}	Surface chlorophyll-a concentration is a proxy for phytoplankton abundance. Peak chlorophyll-a concentration is in July-September while October-December are critical months for juvenile growth and survival.
2.5-year average r-SST IA: S_t, W_t, W_{t+1}, S_{t+1}	Spawning, early survival, and recruitment depend on many cascading factors summarized by the average regional SST over the lifespan of an oil sardine.



Final Covariates

- **Upwelling indices Jul-Sep**
  - Drives productivity
  - At very high levels causes coastal hypoxia
- **Precipitation during the monsoon**
  - River discharge
- **Regional ocean temperature**
  - Physiological effects on growth and survival
- **Ocean climate indices**
  - 2.5 year average regional SST
  - Dipole Mode Index
  - AMO, PDO, ENSO

Statistical models

Time series models

- Catch this year is a function of catch last year

Generalized additive models

- Allow non–linear responses

Dynamic linear models

- Allow effects to vary over time

Oct-Mar Catch ~

s(Oct-June Catch previous year) +
s(July-Sept Catch 2-years previous) +
s(covariate)

Oct-Mar Catch ~

s(Oct-June Catch previous year) +
s(July-Sept Catch 2-years previous) +
beta(t) covariate

No seasonality
One covariate
No Q3(t-1)

Evaluating model and forecast performance

- Adjusted R^2
- AICc – model fit penalized for number of estimated parameters
- **Leave one out cross-validation LOOCV**
  - Leave out a data point
  - Fit model
  - Predict the left out data
  - Median and mean LOOCV errors

Results

Can we improve catch forecasts with environmental data?

What do we mean by "improve"?

Improve over this:

$$catch(t+1) = a + s(catch(t)) + e(t)$$

Complexity is costly

Complexity

Observed catch is some function of the true abundance, effort and catchability

catch(t) = f(abundance(t), effort(t), catchability(t))

Model effort -> $\hat{e}$(t+1)
Model catchability -> $\hat{c}$(t+1)
Model abundance -> $\hat{a}$(t+1)
Estimate f()

We could estimate effort, abundance and catchability to get a forecast

catch(t+1) = $\hat{f}$($\hat{e}$(t+1), $\hat{a}$(t+1), $\hat{c}$(t+1))

Simple

Observed catch can be described as a function of prior observed catch

catch(t+1) = catch(t)

A little more complicated

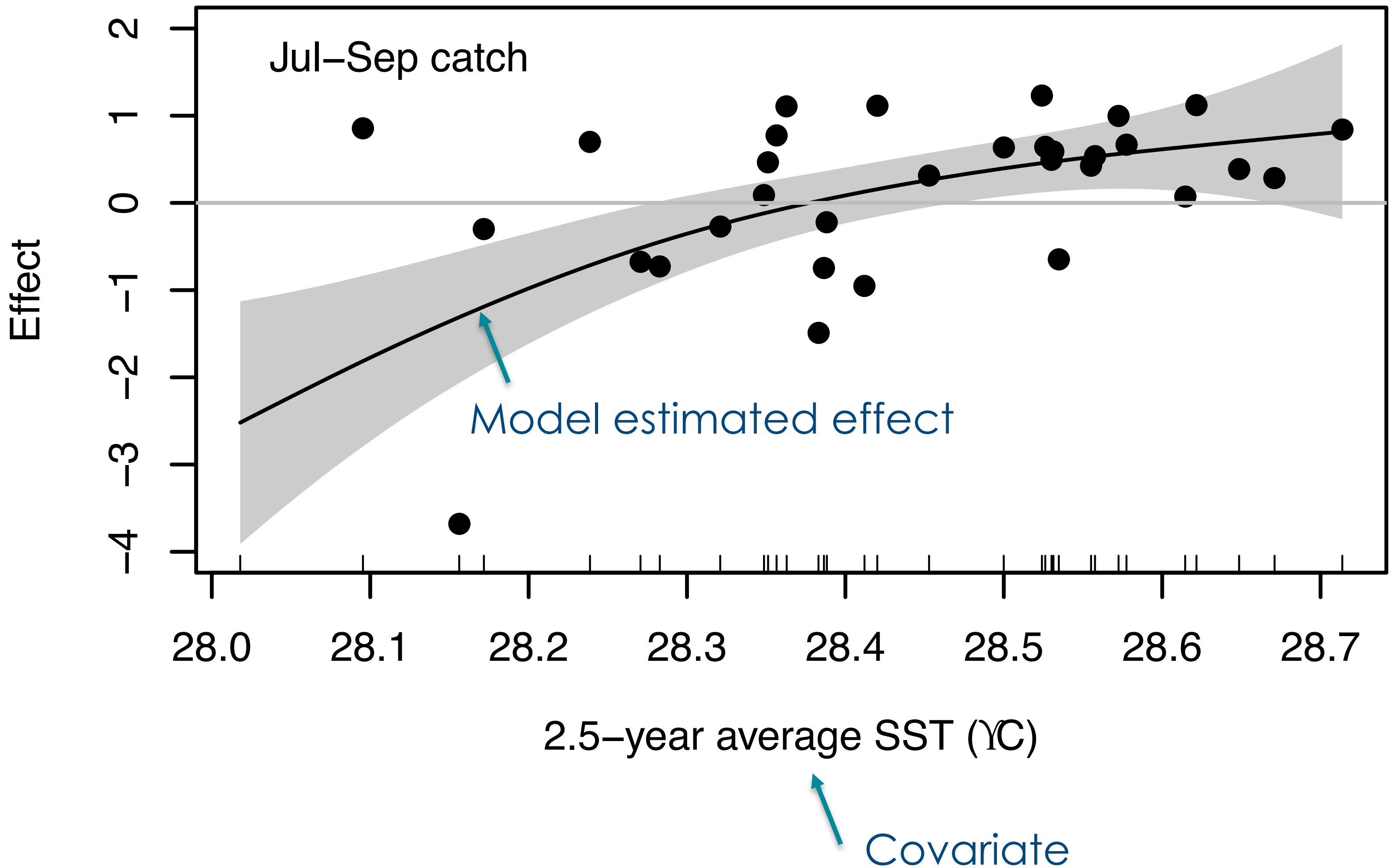
catch(t+1) ≈ g(catch(t))

Estimate g()

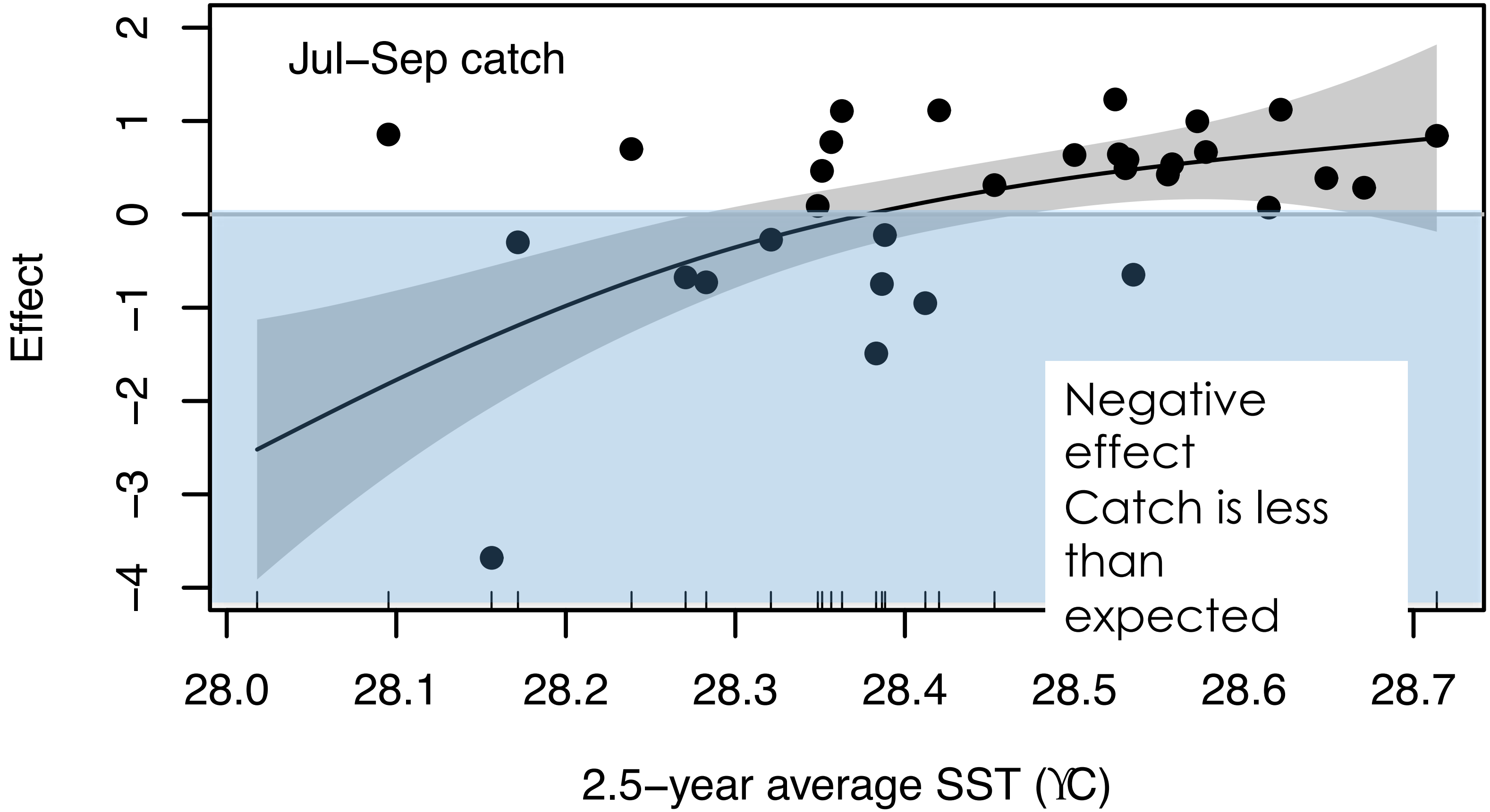
catch(t+1) ≈ $\hat{g}$(catch(t))

What covariates improved forecasts? How?

Covariate effects



Covariate effects



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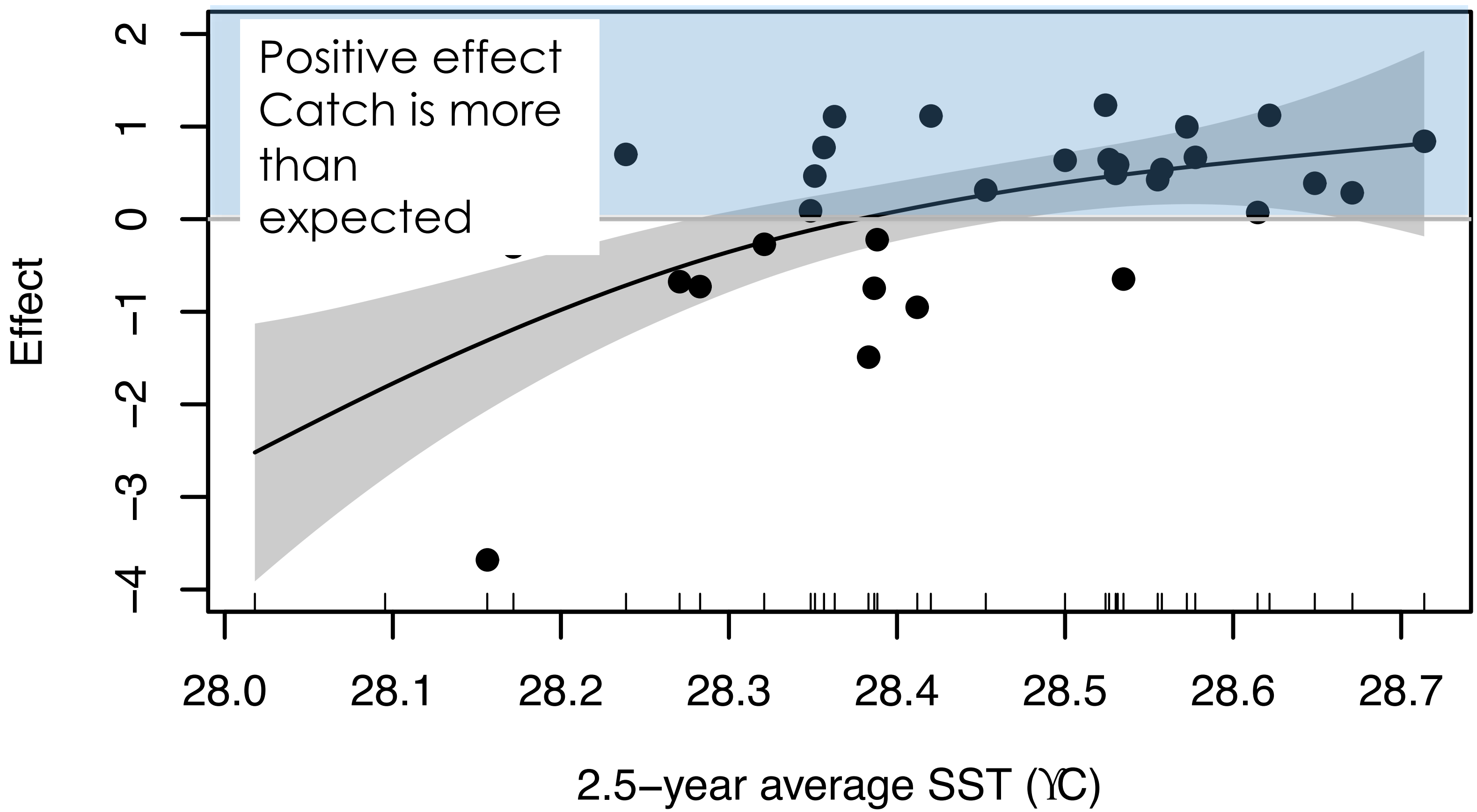
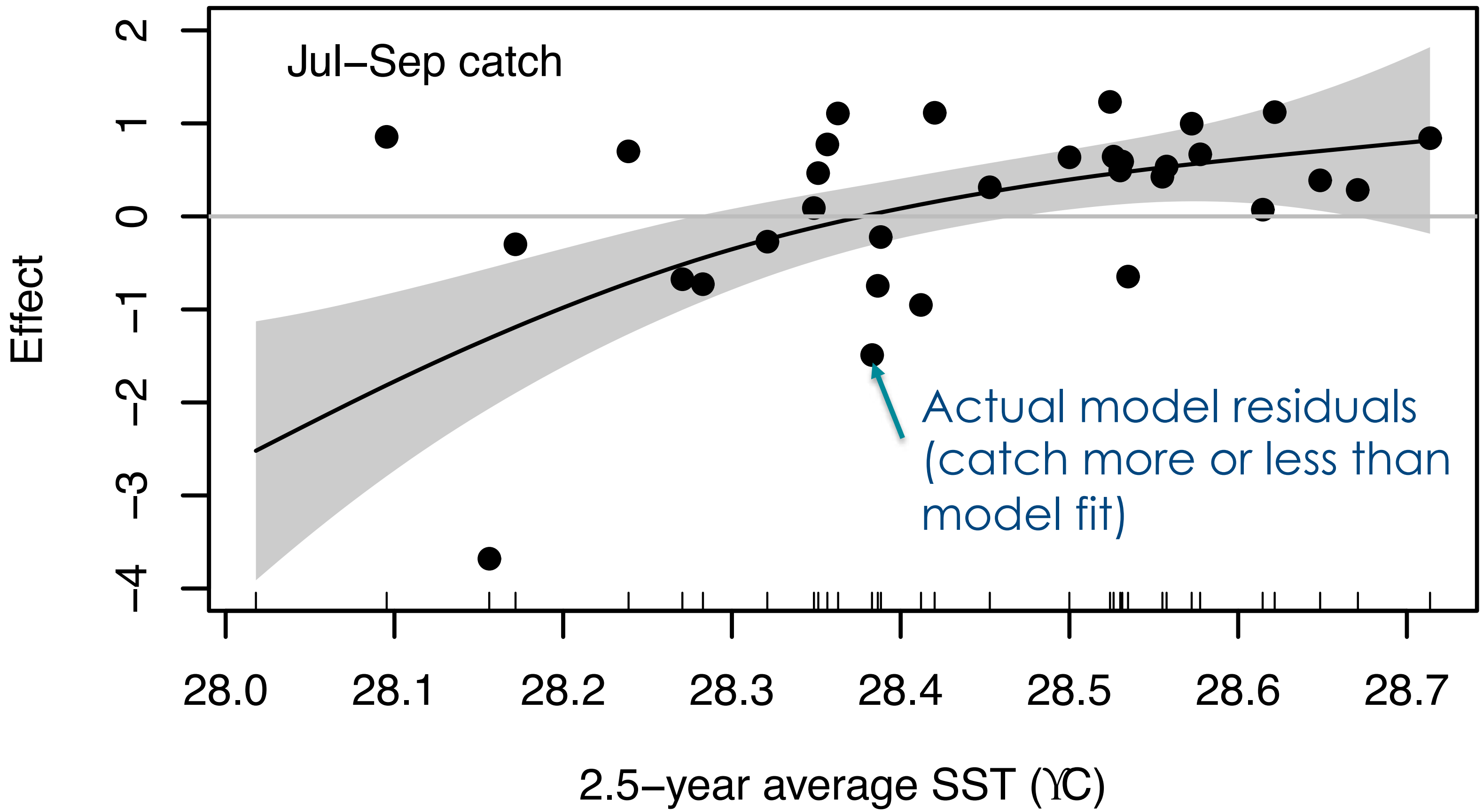
Covariate effects

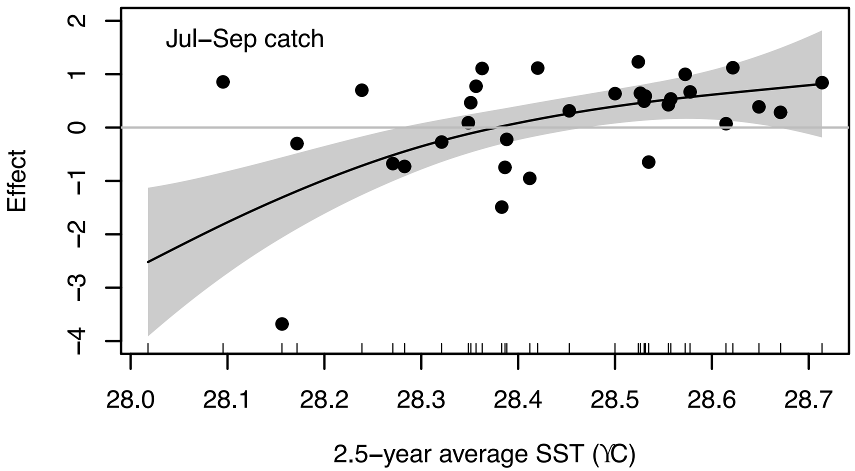


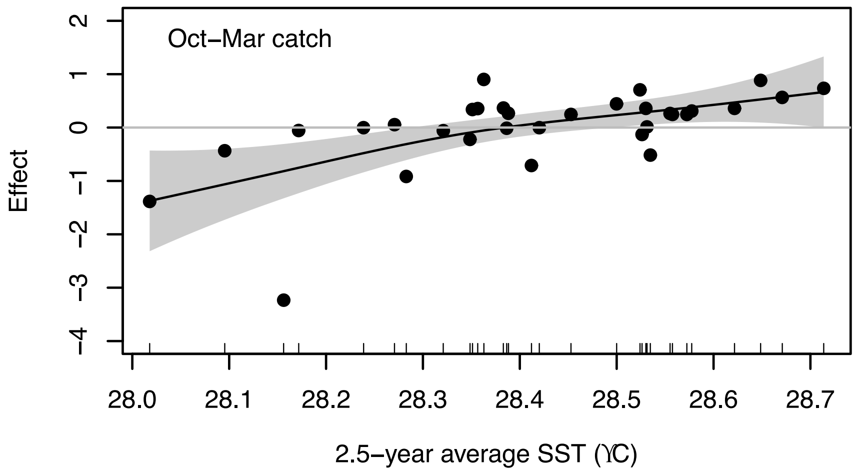
Covariate effects



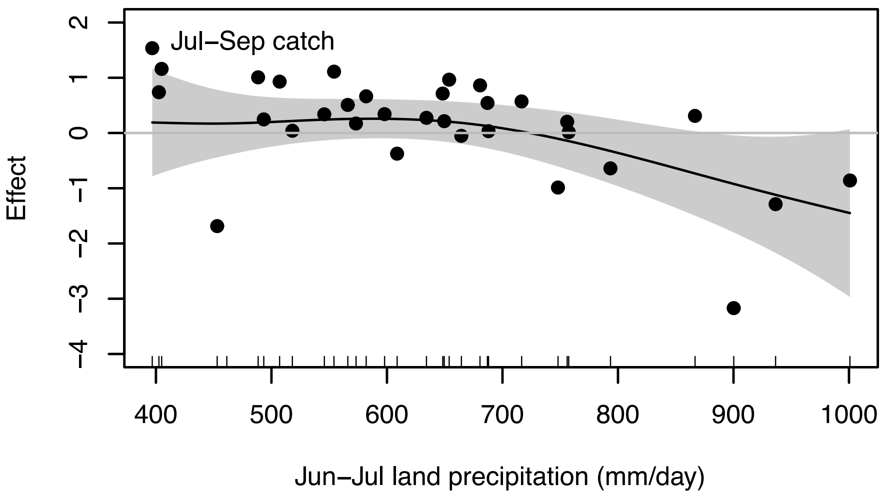
Two covariates were informative

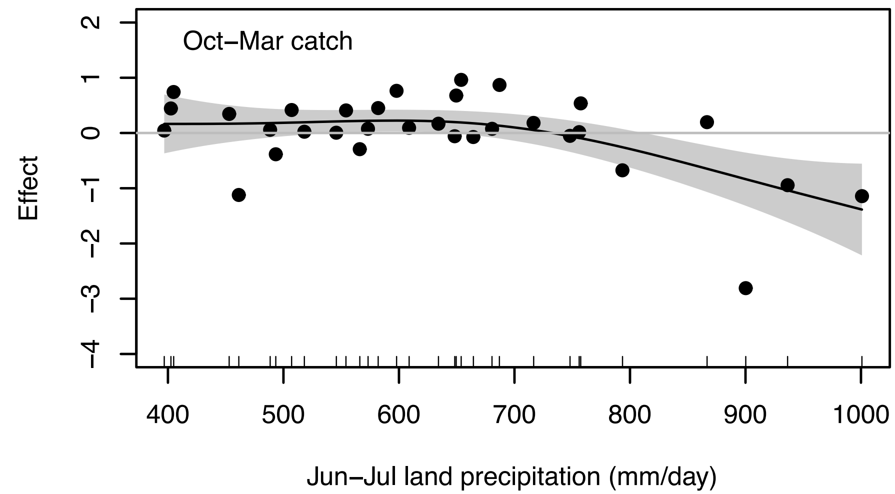
2.5-year average sea surface temperature has a positive effect





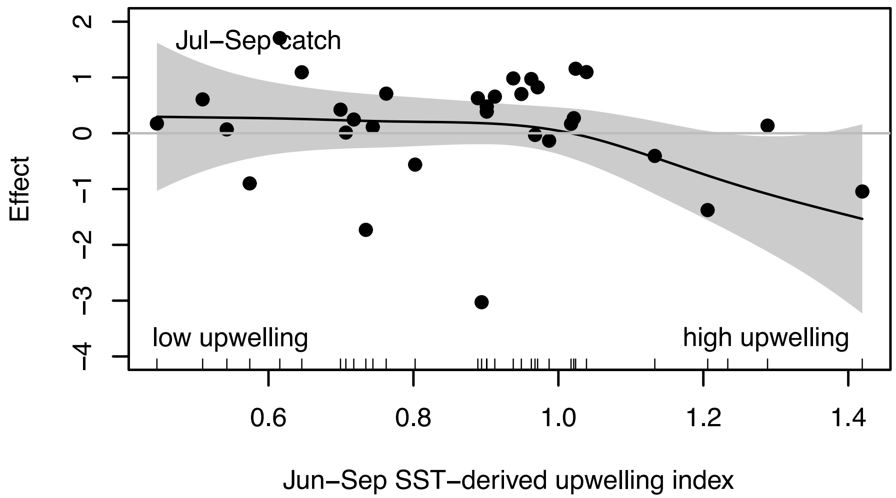
June-July precipitation over LAND the current year appeared as a negative effect on catch later in the year

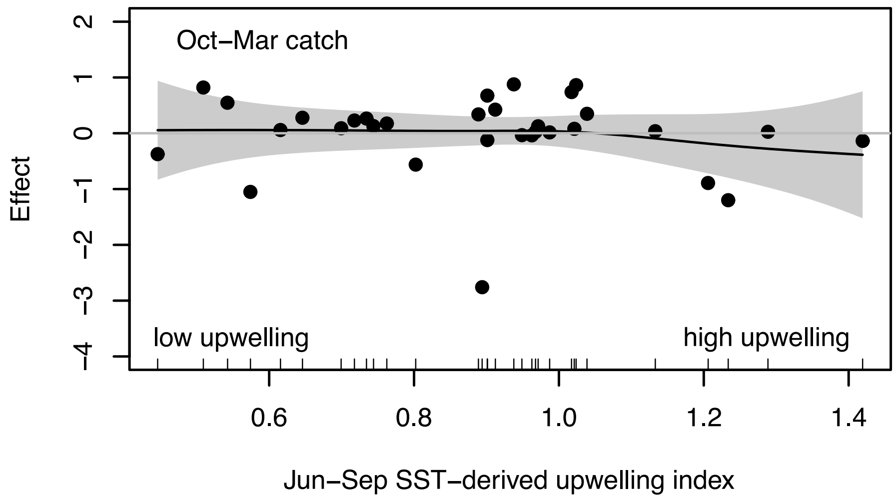




Upwelling wasn't informative

We tried many different indices. All looked roughly flat.

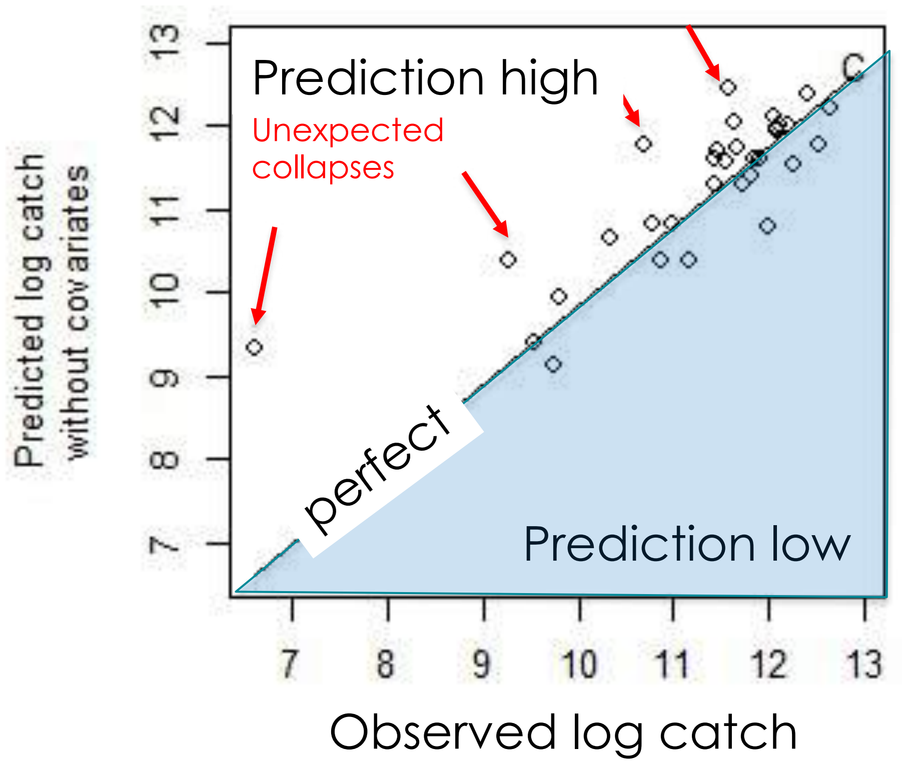




Only effect appeared as a negative effect on the Jul-Sep catch

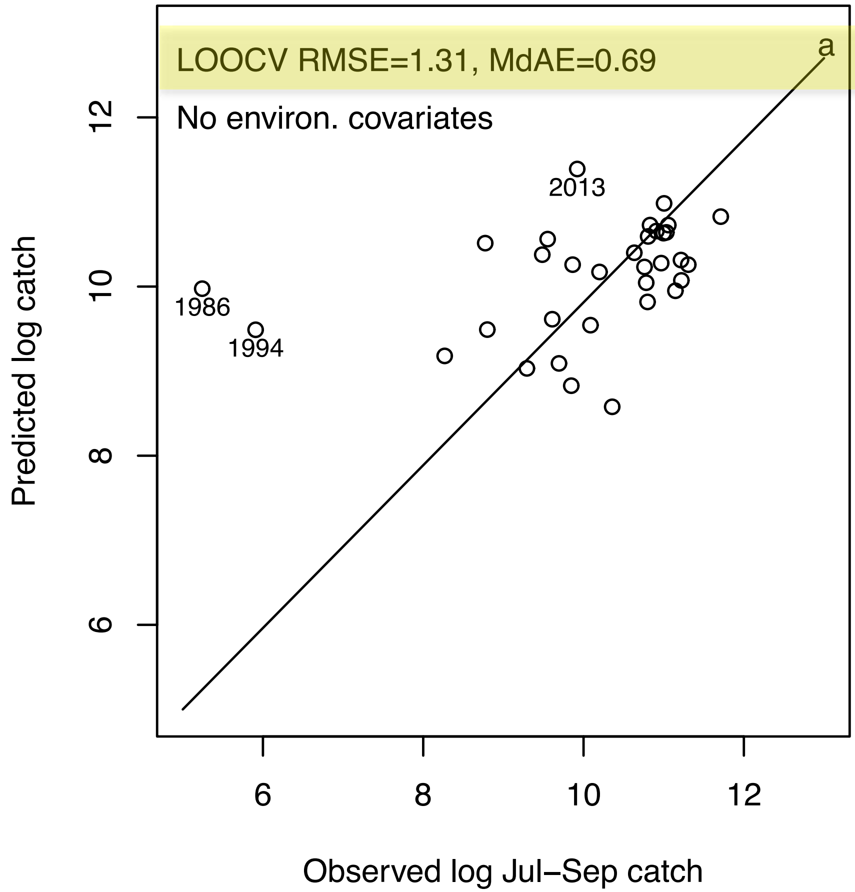
Forecasting the crashes

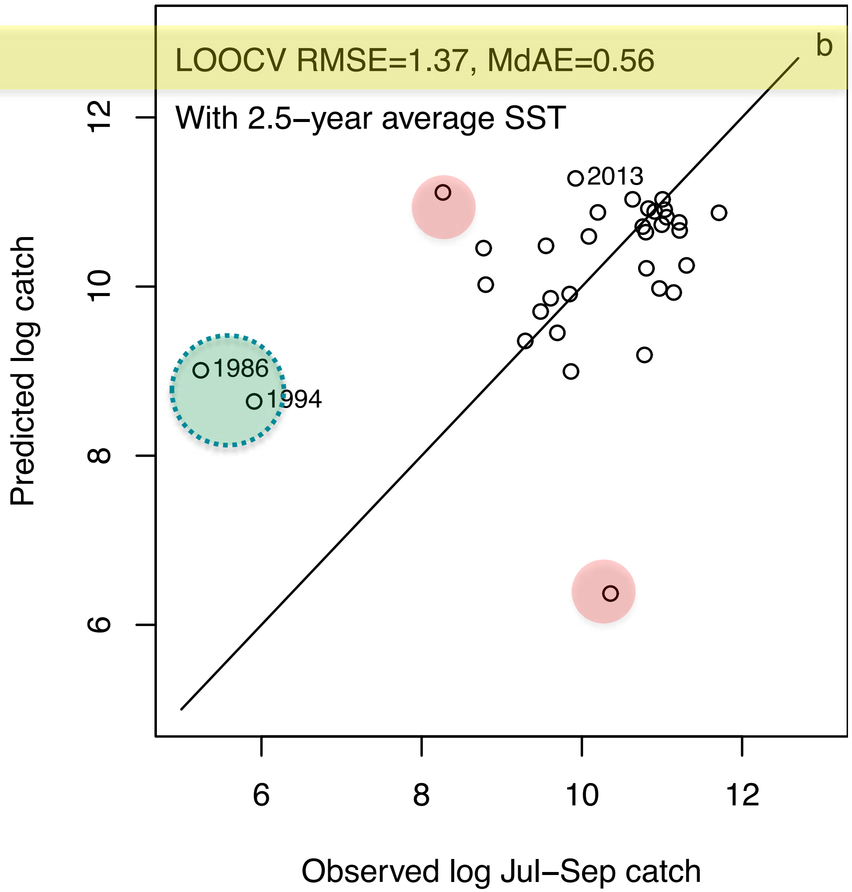
Comparison of observed to predicted catch



These are one-step-ahead predictions not fitted values

Jul-Sep catch is difficult to predict





These plots look very similar with precipitation and AMO.

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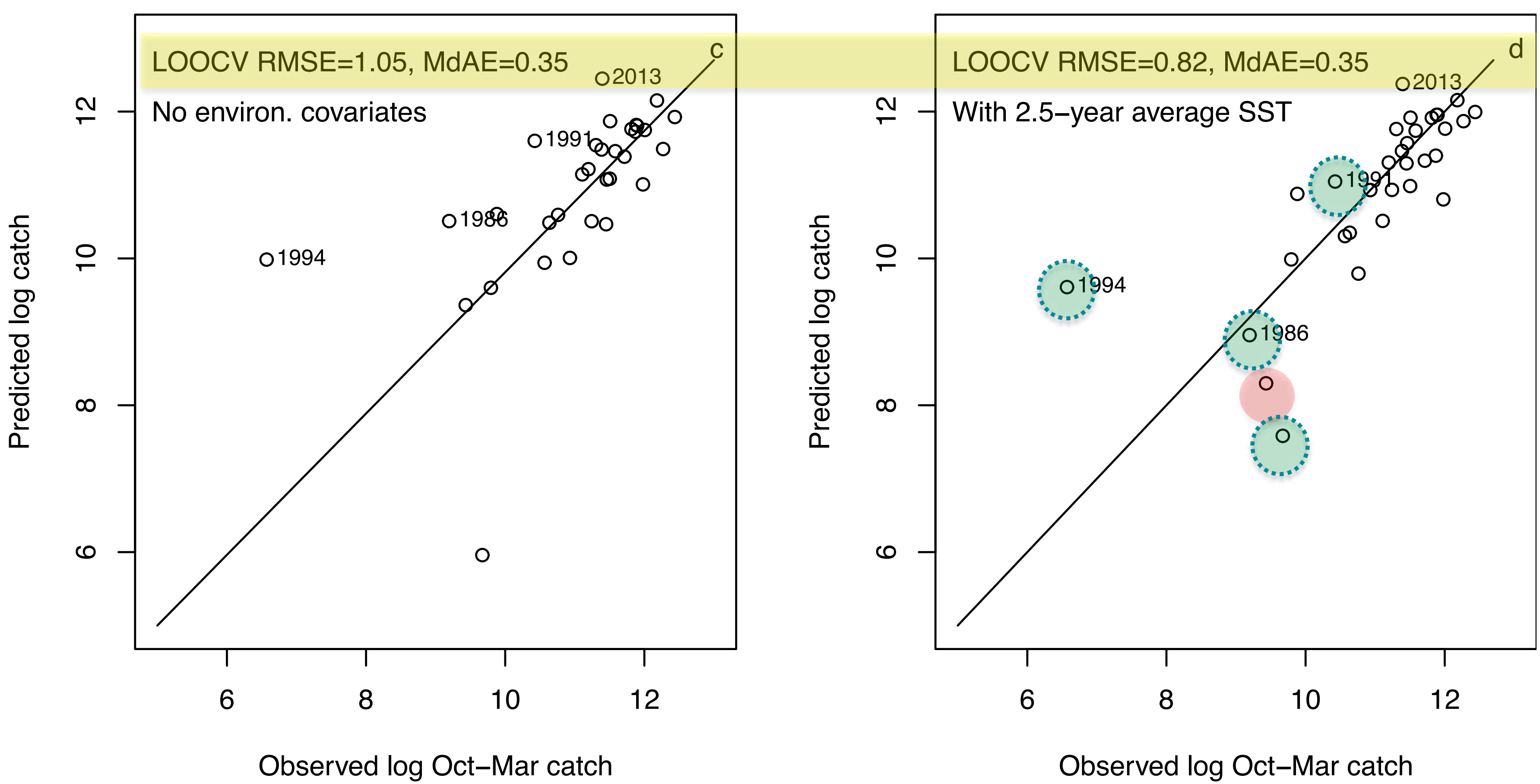
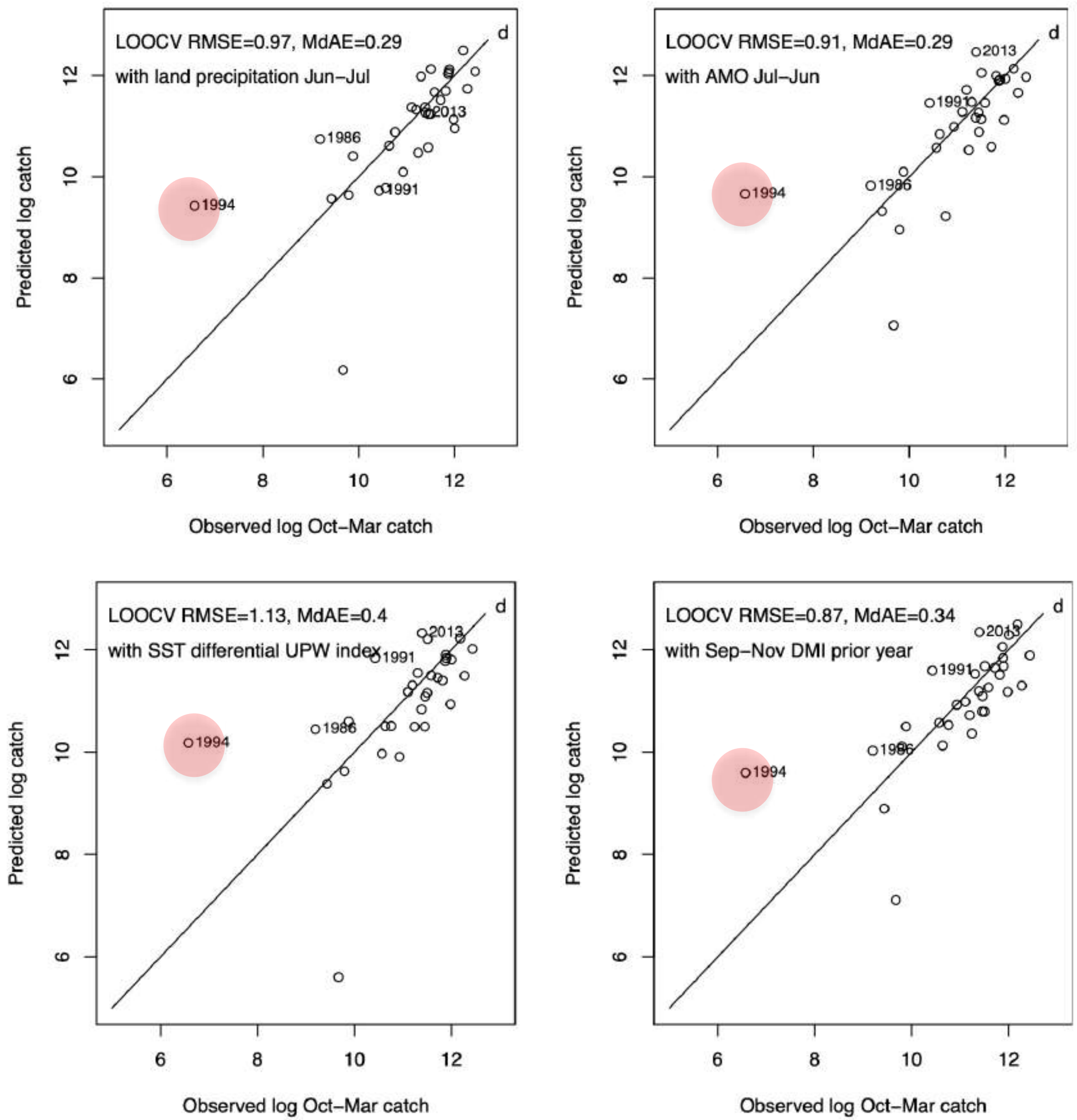
Oct-Mar catch is more predictable



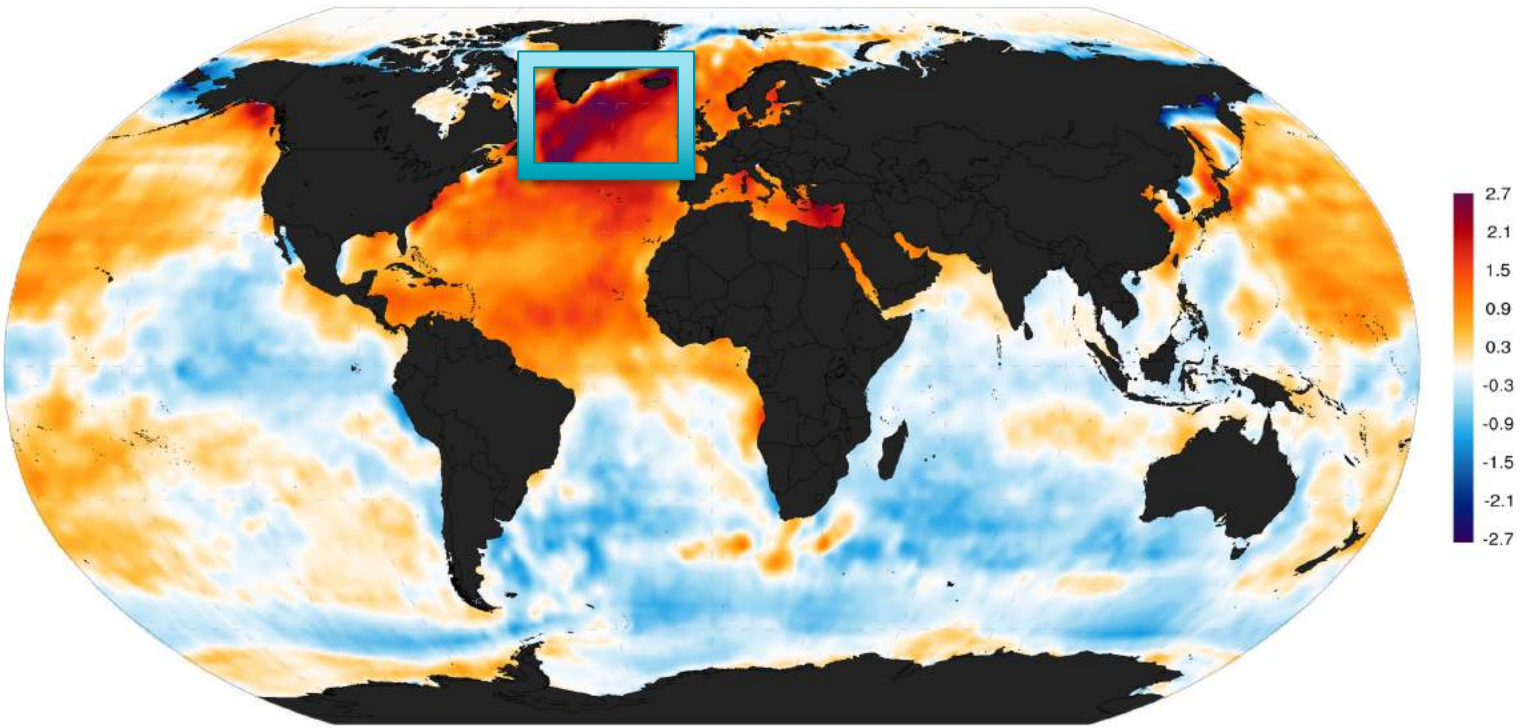
These plots look very similar with precipitation and AMO.

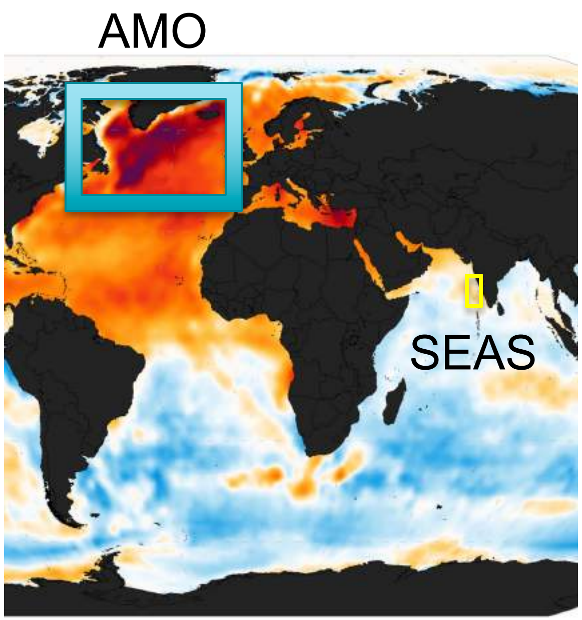
1994 crash was not predicted by any covariate

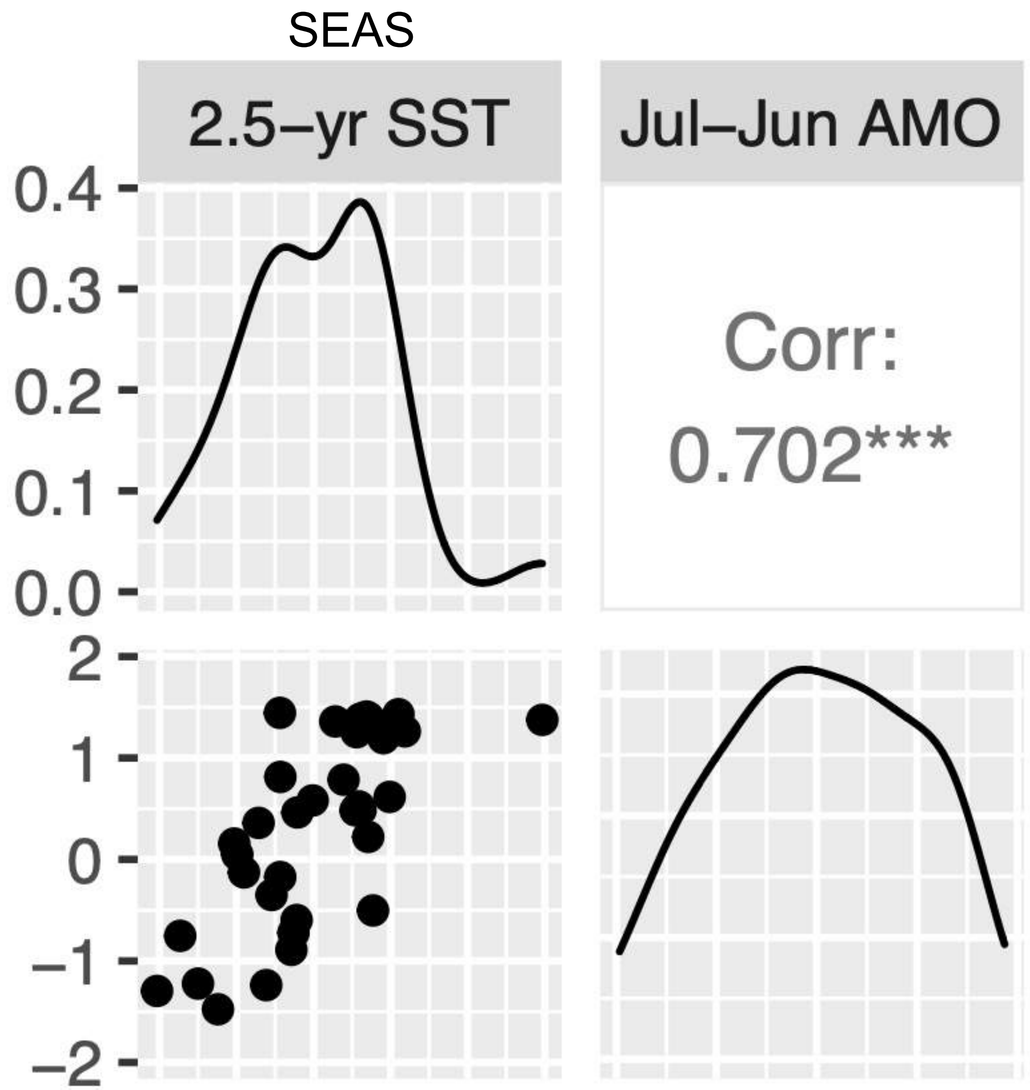


Ocean climate indices

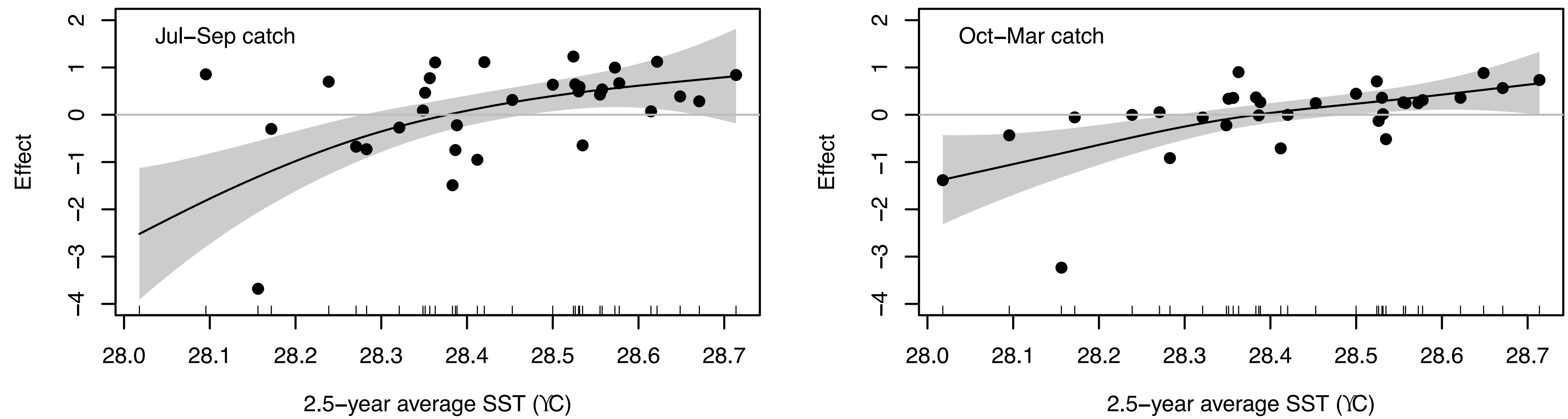
Atlantic multidecadal oscillation index was the only predictive index



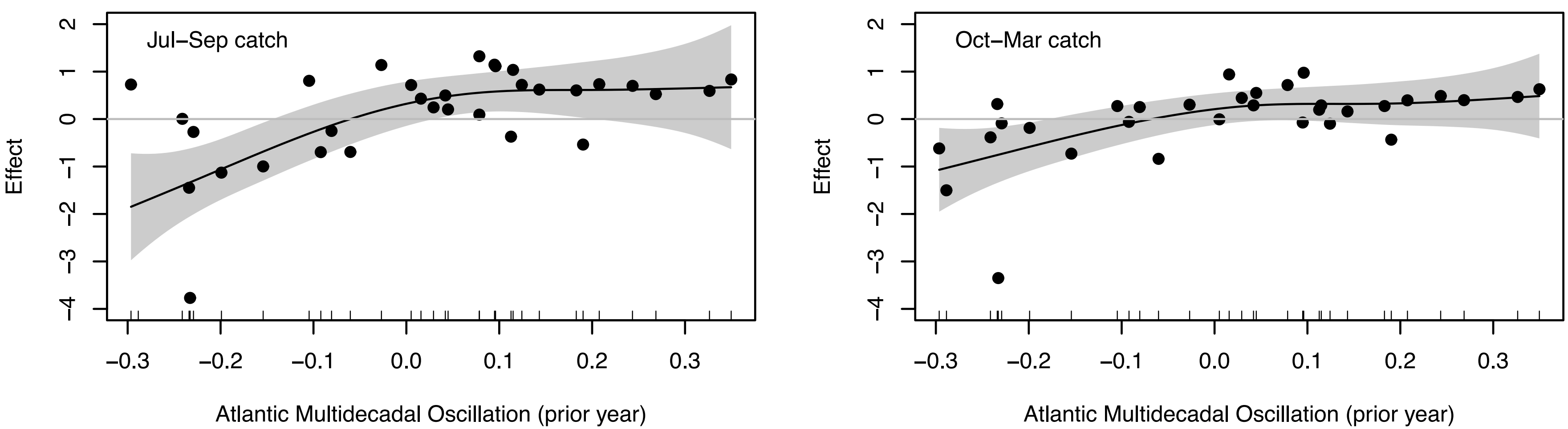

AMO
SEAS


SEAS
2.5–yr SST
Jul–Jun AMO
Corr:
0.702***
0.4
0.3
0.2
0.1
0.0
2
1
0
–1
–2

2.5-year average SEAS sea surface temperature



Jun-Jul Atlantic Multidecadal Oscillation index



Summary main results

- **Temper expectations regarding forecasts**
  - Best model improved forecasts by 20% but still had +/- 40% median and 225% mean errors
- **Covariates assoc. with nearshore low oxygen**
  - High monsoon precipitation over land
  - Extremely high seasonal upwelling
  - Fall Dipole Mode Index
- **Conditions over the sardine lifespan**
  - 2.5-year average regional sea surface temperature
  - AMO

Take-home messages

Acknowledgements

Dr. Usha Varanasi provided the vision and perseverance in initiating and sustaining the collaboration.

The Indian National Centre for Ocean Information Services (INCOIS) and Centre for Marine Living Resources and Ecology (CMLRE) hosted the meetings. **Dr. S.S.C Shenoi** (INCOIS), **Dr. M. Sudhakar** (CMLRE) and **Dr. N. Saravanane** (CMRLE) provided key support (and hospitality). **Dr. Ned Cyr** and **Ed Gorecki** (NOAA) led the NMFS International exchange programs during the study and facilitated the support and the international agreements.

We also thank the many INCOIS, CMLRE, and CMFRI scientists who participated in the research visits and who helped us understand the biology, fishery and fishery data and gave input into the analyses.

The sardine landings data have been collected and analyzed by the Central Marine Fisheries Research Institute (Kochi) since the 1950s. We acknowledge the many researchers involved in this long-term data set.

The **NOAA Fisheries** and the **Indian Ministry of Earth Sciences** jointly provided the financial support for the research.

Final team leads meeting, September 2019

Centre for Marine Living Resources & Ecology, Kochi India