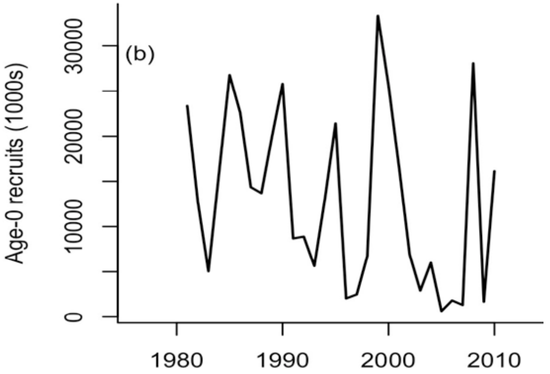
Agenda Item F.2.a
NMFS Report
March 2017

A decade on: re-evaluating oceanographic drivers of California Current sablefish recruitment

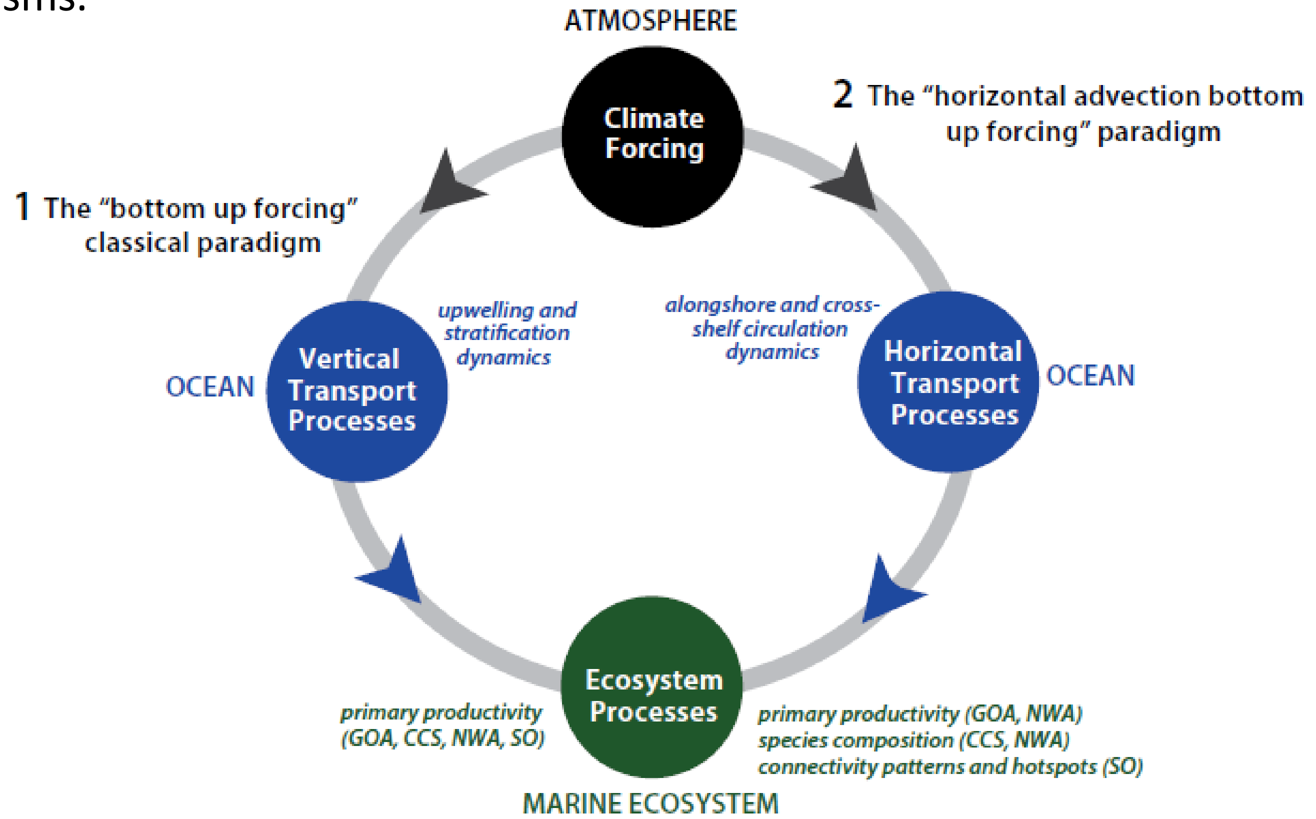


Tolimieri N, Haltuch MA, Qi L, Jacox M, & Bograd S

NOAA FISHERIES
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION

US GLOBEC:
The horizontal-advection bottom-up forcing paradigm

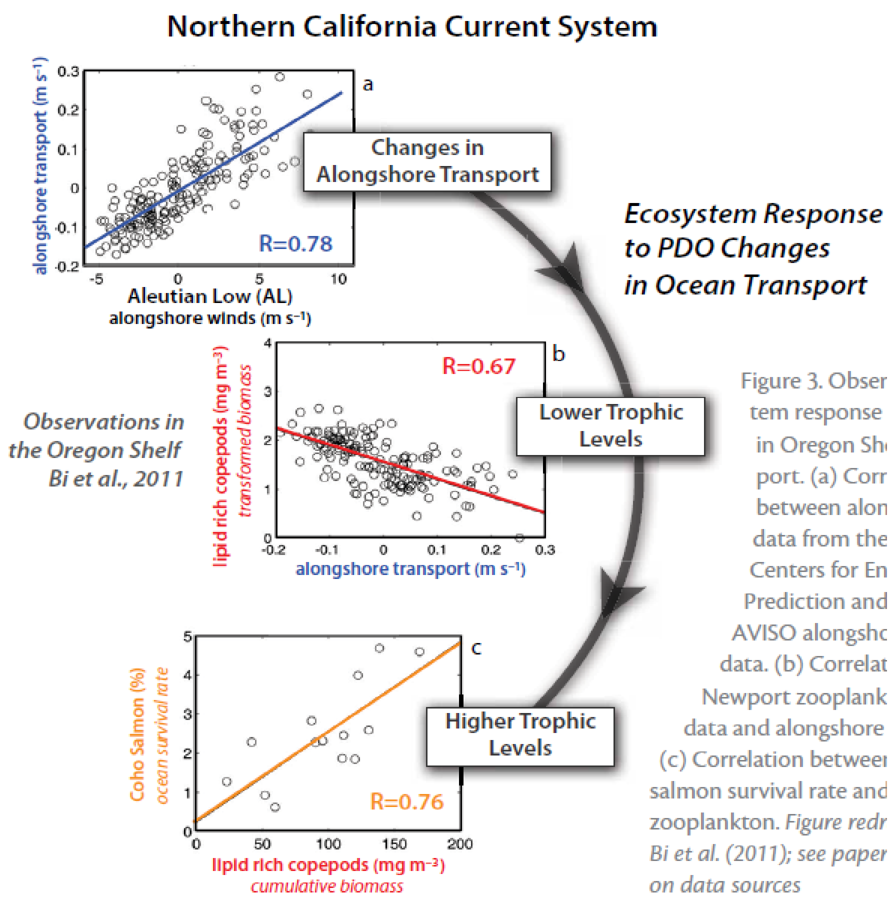
- Large-scale climate forcing drives regional changes in alongshore and cross-shelf ocean transport, directly impacting the transport of nutrients, water masses, and organisms.



Di Lorenzo, et al. 2013. *Oceanography* 26(4):22–33.

US GLOBEC:
The horizontal-advection bottom-up forcing paradigm

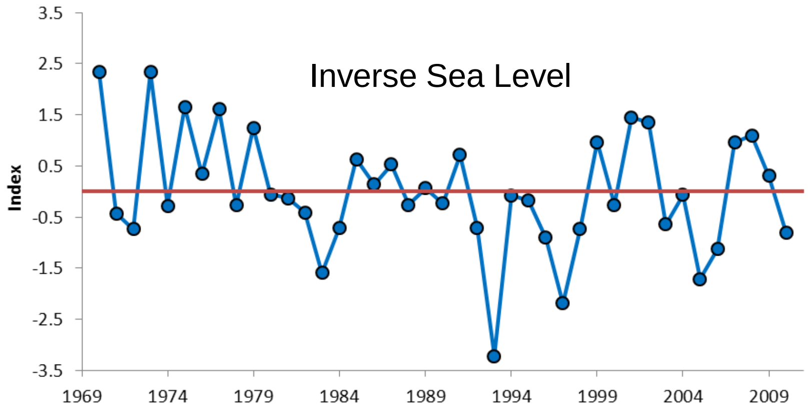
- Framework through which climate variability and change alter sea surface height (SSH), zooplankton community structure, and sablefish recruitment

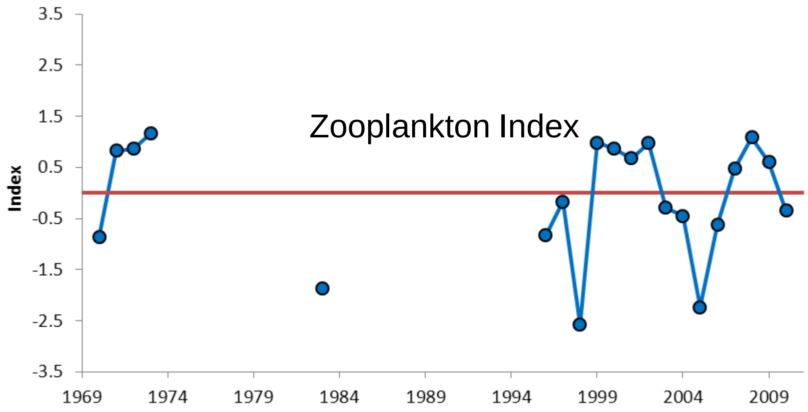


Di Lorenzo, et al. 2013. *Oceanography* 26(4):22–33.

SSH - Sablefish recruitment:
2011 Stock Assessment

- ~35-40% of the variance in recruitment explained
- Continuing validation
  - Bootstrap, jackknife, and removal of recent values
    (Schirripa and Colbert 2006, Schirripa 2007)
  - Randomization tests
    (Stewart et al., 2011)
- Modeled as a survey index of recruitment
  - ~ 1970 - present
  - Uncertainty
  - Missing years of data





SSH - Sablefish recruitment:
2011 Stock Assessment

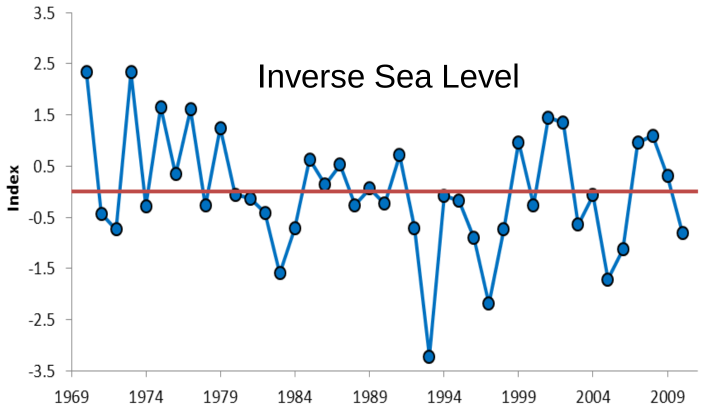
- ~35-40% of the variance in recruitment explained

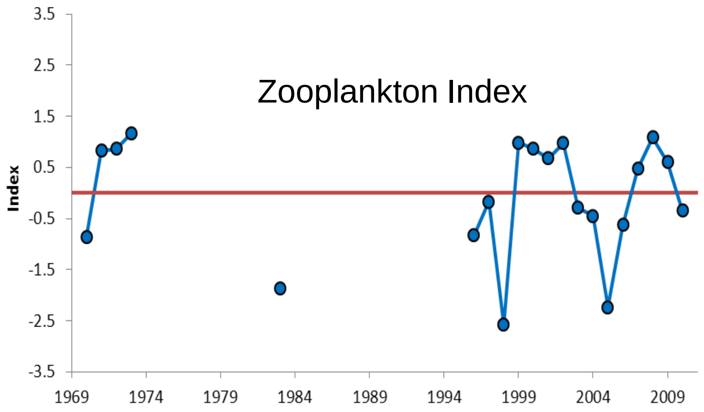
Problem:

- Need to explain > 50% of the recruitment variability to potentially be useful in stock assessment (Basson et al 1999)

Goal

- To improve upon the existing sea level-recruitment relationship
    - Index with higher r^2





Oceanographic drivers of sablefish recruitment

Conceptual life-history

↓

Make hypotheses

↓

Fit a bunch of models (glms)

↓

Log(recruits) =
Intercept + various predictors

↓

Model selection with AICc

↓

Model testing

Literature search

Oceanographic drivers of sablefish recruitment

Conceptual life-history

↓

Make hypotheses

↓

Fit a bunch of models (glms)

↓

Log(recruits) =

Intercept + various predictors

↓

Model selection with AICc

↓

Model testing

Make stage specific & spatially specific hypotheses

- Do not use generalized climate indices like NOI or PDO
- Use ROMS output for oceanic drivers
- Include some biological drivers
  - Predator and prey density
- Include Sea surface height (SSH)
- Spawning stock biomass (SSB)

MORE LATER…

Oceanographic drivers of sablefish recruitment

Conceptual life-history

↓

Make hypotheses

↓

Fit a bunch of models (glms)

↓

Log(recruits) =

Intercept + various predictors

↓

Model selection with AICc

↓

Model testing

Models

Basic glms

- Identity link
- Normal distribution

- Min predictors = 0
- Max predictors = 5

Conceptual life-history model:

Preconditioning to benthic juveniles

Lat: 40-50 ^{o}N
Years: 1980-2010

Life-history stage	Time period	Depth	Sablefish location
Preconditioning	Jun - Dec (Yr 0)	50-1200m with highest occurrence between 150 - 400 m	Bottom
Spawning	Dec (Yr 0)- Mar (Yr 1)	300-500 m	Bottom
Eggs	Jan-Apr	300-825 m with highest occurrence between 240 and 480 m, may rise has high as 200-300 m	Open water
Early Development	Feb-May	1000-1200 m	Open water
Larvae (start feeding)	Feb-May	Surface waters	Open water
Pelagic juveniles	Apr-Nov	Surface waters	Open water
Benthic Juvenile (Age-0)	Aug-Nov	0 - 250 m	Bottom

Conceptual life-history model:

Preconditioning to benthic juveniles

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Eggs		ence 0 m, 00-300	Open water
Early Development			Open water
Larvae (start feeding)			Open water
Pelagic juveniles	Apr-Nov	Surface waters	Open water
Benthic Juvenile (Age-0)	Aug-Nov	0 - 250 m	Bottom

Look at one stage

Conceptual life-history model:

Preconditioning to benthic juveniles

Lat: 40-50 ^{o}N
Years: 1980-2010

Life-history stage	Time period	Depth	Sablefish location
Pelagic juveniles	Apr-Nov	Surface waters	Open water

Hypothesis	Covariates	Depth extent	Longitudinal extent	Data source
(H16) Transport to settlement habitat affects recruitment	Net long-shore transport	Surface waters	0-150 nautical nmi	ROMS
(H17) Transport to settlement habitat affects recruitment	Net cross-shelf transport	Surface waters	0-150 nautical nmi	ROMS
(H18) Growth/Predation hypothesis: Growth rate is faster in warm water leading to reduced time vulnerable to predators etc	Degree days	Surface waters	0-150 nautical nmi	ROMS

Models with ΔAICc < 6.0

Model										R^2	AICc	ΔAICc
Model 1	SSB	CST_{egg}	LST_{ed}		CST_{pjuv}		LST^2_{bjuv}			0.63	77.38	0.00
Model 2	SSB	CST_{egg}	LST_{ed}		CST_{pjuv}	LST_{bjuv}				0.60	79.71	2.33
Model 3	SSB	CST_{egg}			CST_{pjuv}		LST^2_{bjuv}			0.53	81.33	3.94
Model 4	SSB	CST_{egg}			CST_{pjuv}		LST^2_{bjuv}		DD_{bjuv}	0.57	82.07	4.69
Model 5	SSB	CST_{egg}	LST_{ed}		CST_{pjuv}			CST_{bjuv}		0.57	82.15	4.76
Model 6	SSB	CST_{egg}		DD_{larv}	CST_{pjuv}		LST^2_{bjuv}			0.56	82.95	5.56
Model 7	SSB	CST_{egg}	LST_{ed}		CST_{pjuv}					0.50	83.11	5.72
Model 8	SSB				CST_{pjuv}		LST^2_{bjuv}			0.44	83.35	5.97

One best-fit model

Model						R^2	AICc	ΔAICc
Model 1	SSB	CST_{egg}	LST_{ed}	CST_{pjuv}	LST^2_{bjuv}	0.63	77.38	0.00

<u>**One model with ΔAICc < 2.0 r^2 = 0.63**</u>

SSB

Cross-shelf transport – egg stage 500 m off shore to 170 nmi
300-825 m

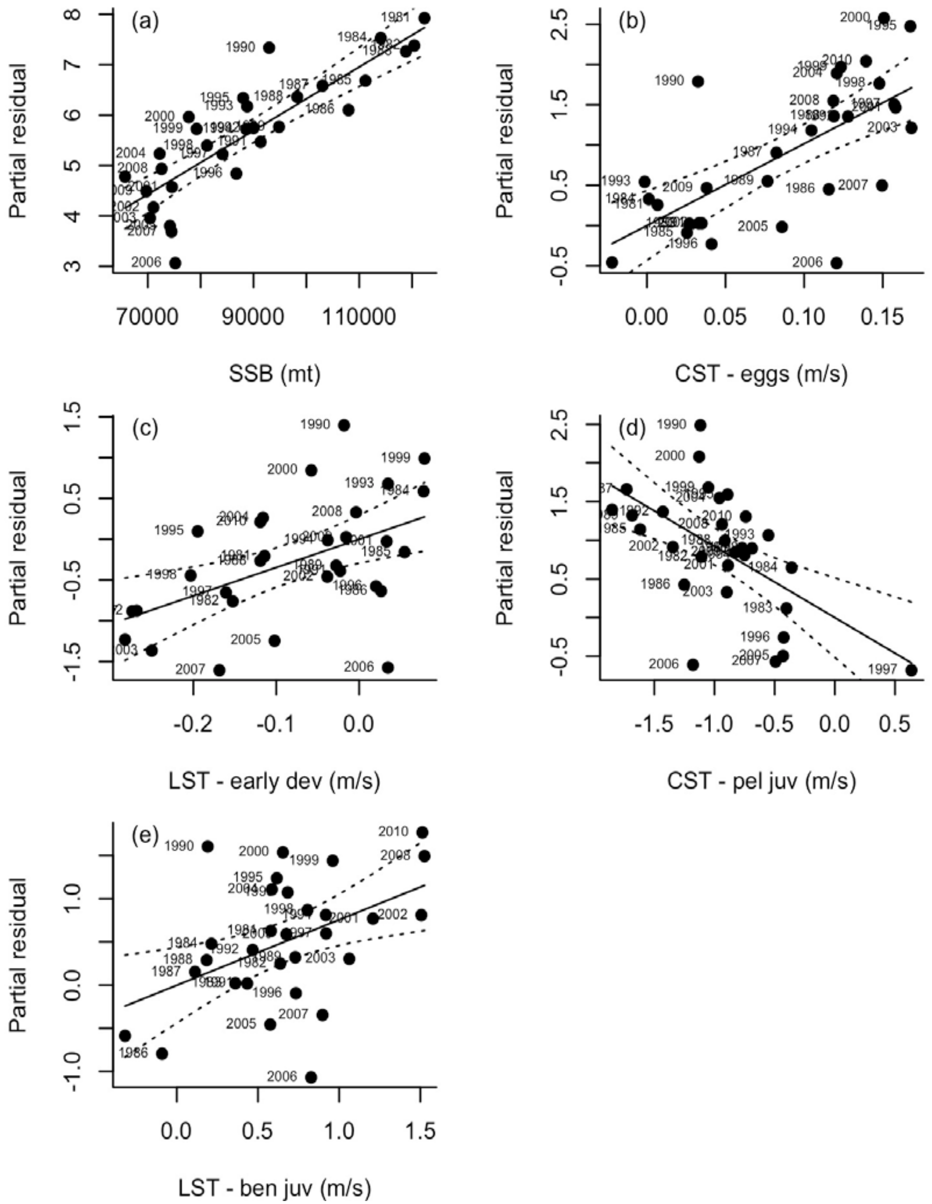
Long-shelf transport – early development 1000 m off shore to 170 nmi
1000 – 1200 m

Cross-shelf transport – pelagic juvenile stage surface waters out to 150 nmi

Long-shore transport – benthic juveniles (^2) bottom
0-250 m

Partial residual plots

Residuals + $\hat{\beta}_i X_i$ versus X_i



Multicolinearity among predictor variables?

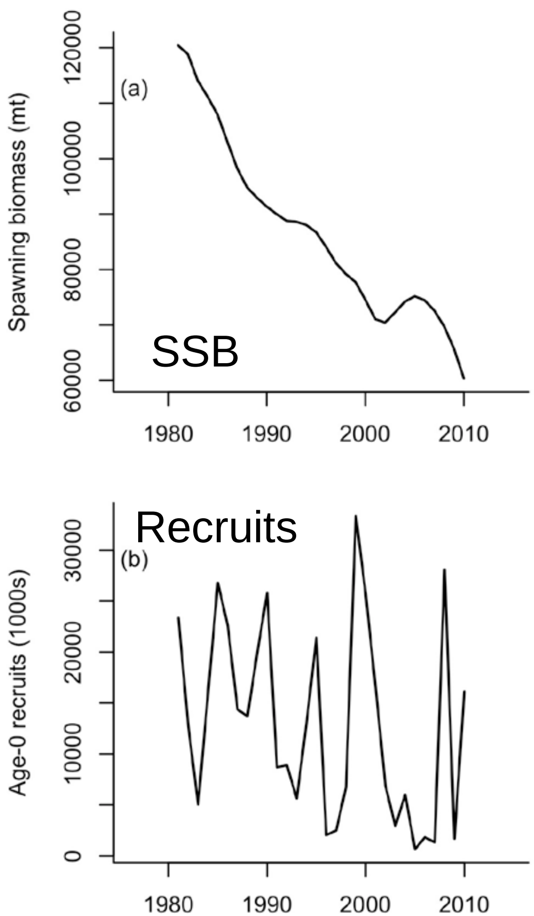
	SSB	CST_{egg}	$LST_{early\ dev}$	$CST_{pel\ juv}$	VIF
SSB	--				2.48
CST_{egg}	$\boxed{-0.60}$				1.92
$LST_{early\ dev}$	-0.07	-0.29			1.23
$CST_{pel\ juv}$	-0.11	0.14	-0.11		1.03
$LST_{ben\ juv}$	$\boxed{-0.69}$	0.36	0.00	0.25	1.64

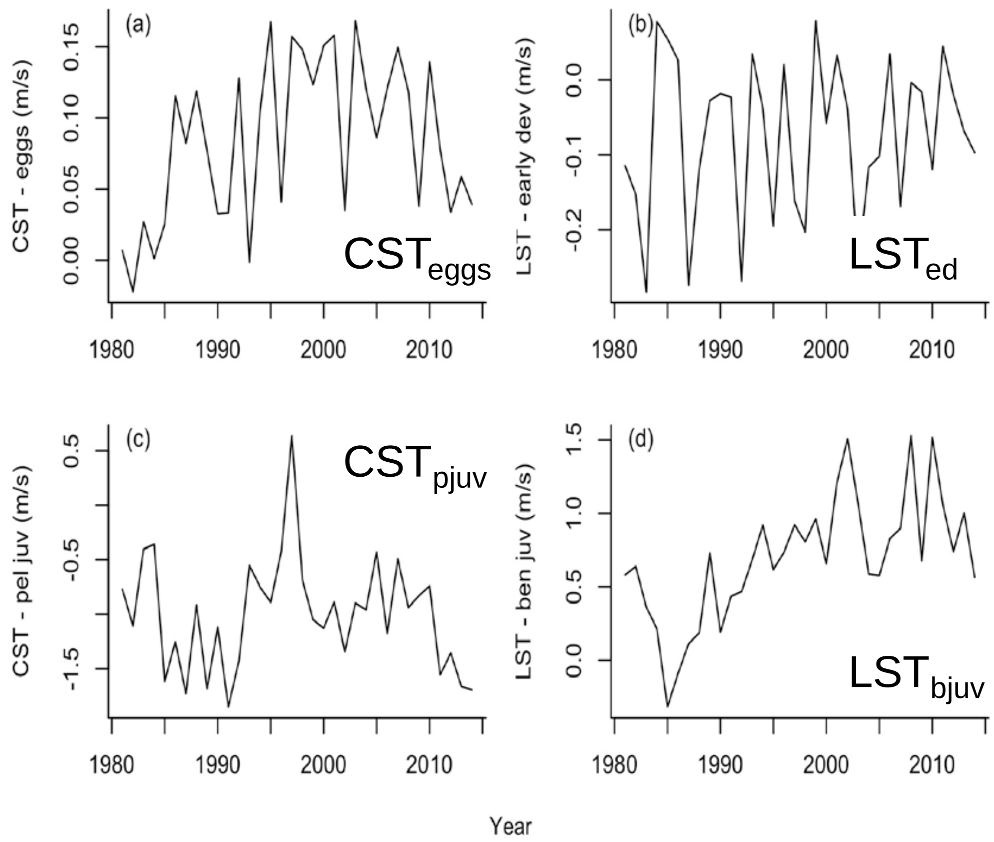
VIF = variance inflation factor

< 1: low
1-5: moderate
> 5: large

Ok, but a little high

Covariates in the best-fit model





SSB, CST_{egg} & LST_{bjuv} show long-term trends (to varying extents)

Model testing

Best-fit model

(1) Resample w/replacement individual recruitment values to estimate expected r^2 values for randomized data (1000 reps)

(2) Bootstrapping to estimate bias and calculate standard error of the parameter estimates (1000 reps)

(3) Jackknife resampling to determine effect of any single year

(4) Resampled the recruitment values for each year (1000 reps)

   a) Log-normal distribution

   b) Mean = value for that year

   c) Recruitment SD by year from stock assessment

Whole model fitting process – do we get the same model?

(5) Rerun excluding one year each time

(6) Re-sampled the sablefish recruitments with error (as in Step 4 above) and compared top models from each run (100 reps)

Model testing

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5-covariates

$r^2 = 0.15$

(95% CI: 0.03 – 0.38

Model testing

Best-fit model

(1) Resample w/replacement individual recruitment values to estimate expected r^2 values for randomized data (1000 reps)

(2) Bootstrapping to estimate bias and calculate standard error of the parameter estimates (1000 reps)

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5-covariates

$r^2 = 0.15$

95% CI: 0.03 – 0.38

Median $r^2 = 0.67$

95% CI: 0.42 – 0.84

Model testing

Best-fit model

(1) Resample w/replacement individual recruitment values to estimate expected r^2 values for randomized data (1000 reps)

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5-covariates

$r^2 = 0.15$

95% CI: 0.03 – 0.38

Median $r^2 = 0.67$

95% CI: 0.42 – 0.84

Median $r^2 = 0.63$

95% CI = 0.59 – 0.70

Model testing

Best-fit model

(1) Resample w/replacement individual recruitment values to estimate expected r^2 values for randomized data (1000 reps)

(2) Bootstrapping to estimate bias and calculate standard error of the parameter estimates (1000 reps)

(3) Jackknife resampling to determine effect of any single year

(4) Resampled the recruitment values for each year (1000 reps)

a) Log-normal distribution

b) Mean = value for that year

c) Recruitment SD by year from stock assessment

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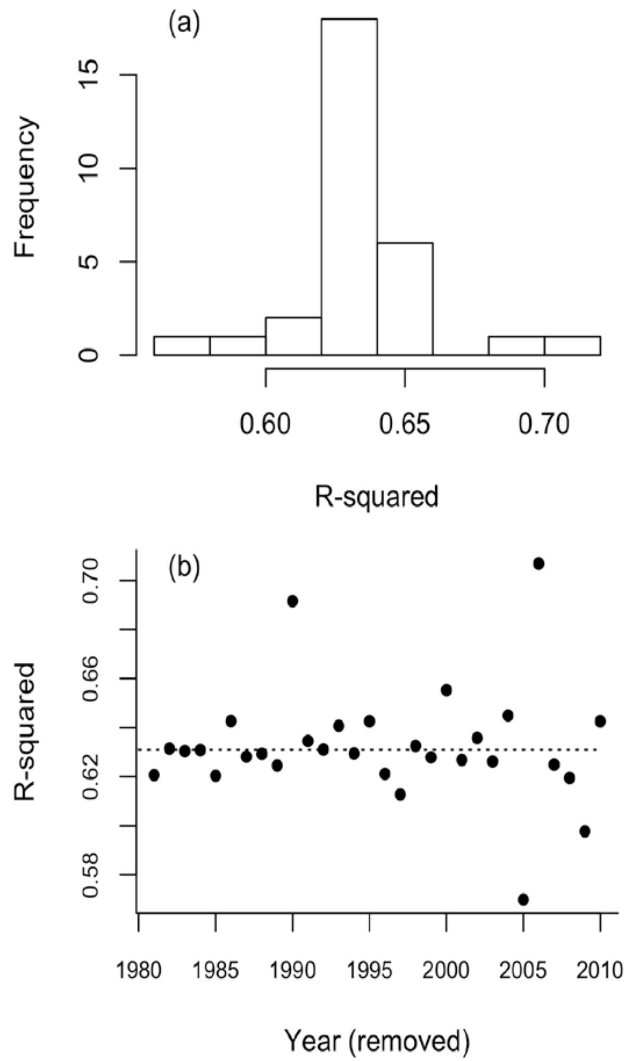

Model testing

Without 2007 data get different model

Covariates						R2	AICc	ΔAICc
SSB			CST_{larvae}	SSH		0.56	71.35	0.00
SSB			CST_{larvae}		SSH^2	0.56	71.57	0.22
SSB		CST_{eggs}	CST_{larvae}	SSH		0.59	72.48	1.13
SSB		CST_{eggs}	CST_{larvae}		SSH^2	0.59	72.89	1.54
SSB	MLD_{sd}		CST_{larvae}	SSH		0.58	73.18	1.83

Whole model fitting process – do we get the same model?

(5) Rerun excluding one year each time (n = 30)

(6) Re-sampled the sablefish recruitments with error (as in Step 4 above) and compared top models from each run (100 reps)

Removing 2007 results in a different best-fit model

5 models with ΔAICc < 2.0

CST_{larvae} & SSH

replace

CST_{eggs}, LST_{edev}, CST_{pjuv}, LST_{bjuv}

$r^2 = 0.56$

Std Coefs

SSB = 0.422

CST_{larvae} = 0.476

SSH = -0.358

Model testing

CST_{larvae} (Feb – May) overlaps CST_{pjuv} (Apr – Nov)

Perhaps CST in April-May CST is important?

SSH correlated with CST_{pjuv} ($r = 0.56$)

CST_{larvae} & SSH

replace

CST_{eggs}, LST_{edev},
CST_{pjuv}, LST_{bjuv}

Whole model fitting process – do we get the same model?

(5) Rerun excluding one year each time

(6) Re-sampled the sablefish recruitments with error (as in Step 4 above) and compared top models from each run (100 reps)

Model testing

Best-fit model

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(2) Bootstrapping to estimate bias and calculate standard error of the parameter estimates (1000 reps)

(3) Jackknife resampling to determine effect of any single year

(4) Resampled the recruitment values for each year (1000 reps)

   a) Log-normal distribution

   b) Mean = value for that year

   c) Recruitment

Whole model fitting process – do we get the same model?

(5) Rerun excluding one year each time

(6) Re-sampled the sablefish recruitments with error (as in Step 4 above) and compared top models from each run (100 reps)

100 refits

- 93 out of 100 cases top model was the same
- In 7 cases, DD_{bjuv} replaced $LST_{early\ dev}$

Update with 2011 – 2014 data?

➔ **We used data for 1980 – 2010**

➔ **2011 – 2014 data are available from a different ROMS model**

Refit best-fit model from 1980-2010

With

1980 - 2014

Update with 2011 – 2014 data?

- ➔ **We used data for 1980 – 2010**
- ➔ **2011 – 2014 data are available from a different ROMS model**

Refit best-fit model from 1980-2010

With

1980 - 2014

$r^2 = 0.49$

Update with 2011 – 2014 data?

➔ **We used data for 1980 – 2010**

➔ **2011 – 2014 data are available from a different ROMS model**

<u>Inconsistencies between the two models:</u>

- Inputs from different products
  - Surface forcing (heat flux, wind)
  - Ocean boundary conditions
- For variables that are well observed confident that the two models are consistent
  - SST, SSH, MLD
- But not possible to validate many of our predictors between models
- New time series are short

So What's Next?

- What to do about physical time series
  - Single reconstruction as far back as possible and which can be updated into the future
- Short term forecasting applications for management advice.
  - Leading indicator – dependent on forecasting important covariates: JSCOPE?
- Go back in time – what could recruitment have looked like?
  - Recruitment hind-casting.
- MSE can be used to evaluate the robustness of control rules to potential long term trends in recruitment-climate relationships