

Oceanographic Drivers of northern Yellowtail

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Northern Yellowtail Recruitment

Fully informed recruitment deviations from the 2017 northern Yellowtail stock assessment (Taylor et al. 2017) begin around 1976/1977. Recruitment deviations are available through 2014, but information quality starts to go down around 2010/2011. This can be seen in Figure 1 where the uncertainty increases dramatically in 2011. Oceanographic data from GLORYs is first available in 1993. For the purposes of this investigation, model fitting was performed using data from 1993 - 2014. Notably, the decline in information quality can have an influence on the model selection process, particularly cross validation approaches that leave out the last 5 or 10 years.

Oceanographic indicators of northern Yellowtail

Darby et al. In Prep examined the relationship between recruitment deviations from the 2017 northern Yellowtail rockfish assessment (Taylor et al. 2017) following methods of Haltuch et al. 2020. The oceanographic conditions investigated (Table 1) were based on an extensive literature review of conditions impacting northern Yellowtail rockfish throughout different

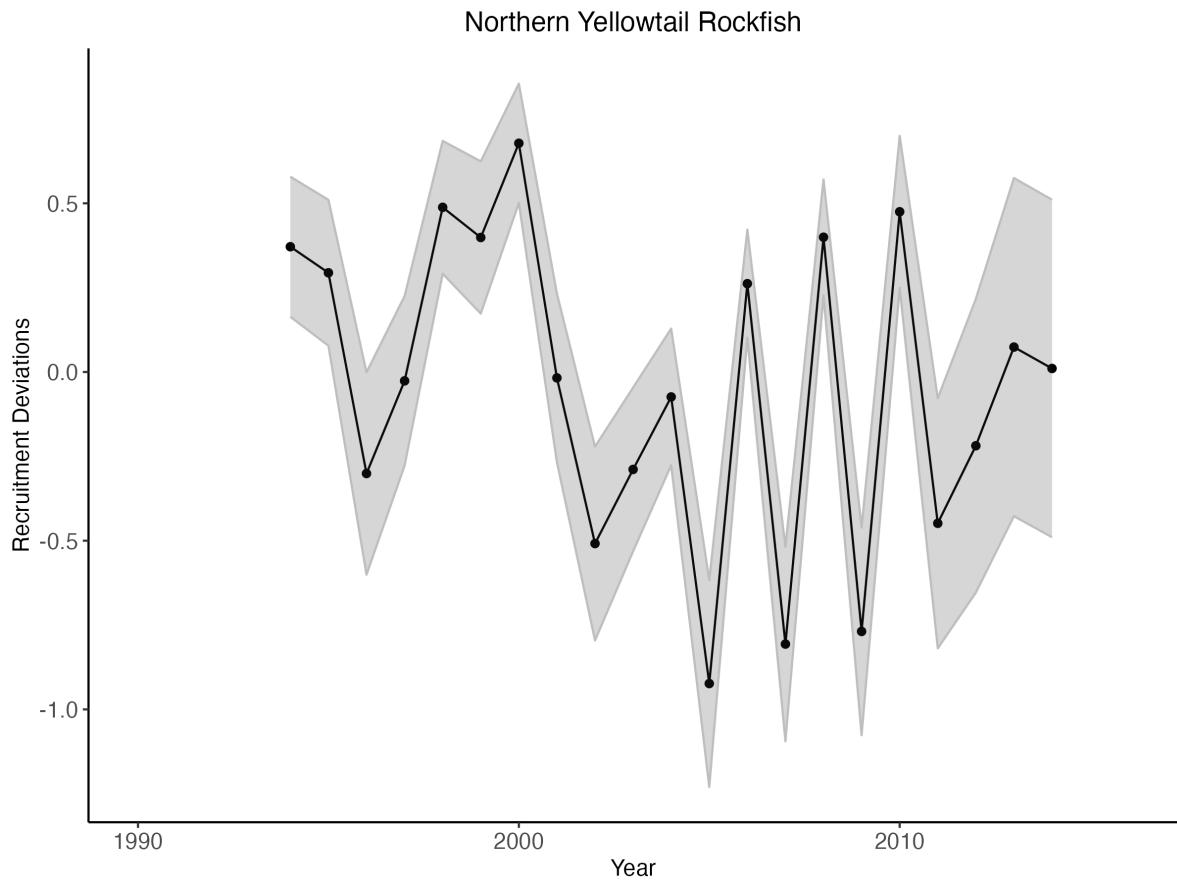


Figure 1: Norhtern Yellowtail rockfish recruitment deviations from 1993 - 2014. Shaded region represents 2 SEs

lifestages linked to recruitment. Previous assessments used Regional Ocean Modeling System (ROMS) but Petrale 2023 identified inconsistencies in oceanographic conditions impacting groundfish recruitment. We used an alternative model, Global Ocean Physics Reanalysis (GLORYS), for conditions that were identified to have inconsistencies in the 2023 Petrale Sole assessment (citation) and which was used for the 2024 Pacific hake assessment (citation). Upwelling conditions were not available from GLORYs and thus a ROMs upwelling time series were used.

The study area encompassed the region from 40N – 48N in the California Current Ecosystem with individual predictors limited by depth and/or distance from the shore (Table 1). Model selection resulted in a single model with four oceanographic variables explaining 65% of the deviation in recruitment deviations. Recruitment deviations were:

- (1) Negatively associated with later spring transition of the upwelling season derived from the Coastal Upwelling Transport Index (CutSTI_{pjuv})
- (2) Recruitment is maximized when mixed layer depth at the larval stage (MLD_{part}) is one standard deviation above average
- (3) Recruitment is maximized when HCI during the larval stage (HCII_{larv}) is at average values
- (4) Recruitment is maximized when long-shore transport during the larval stage (LST_{larv}) is above or below average.

These results indicate that output from oceanographic models might be a useful basis for an environmental index of recruitment for northern Yellowtail rockfish to allow for better model precision and near-term forecasting. Single oceanographic conditions that are most important for northern Yellowtail recruitment vary through time, and as a result so does the predictive capacity of individual predictors. This highlights the values of using multiple environmental conditions in a single index, but also the challenge in appropriately specifying models and evaluating performance.

Oceanographic predictors of northern Yellowtail recruitment

Oceanographic conditions (Table 1) linked to northern Yellowtail recruitment fall into three primary categories: temperature, transit, and upwelling (Figure 2), many of which covary within each grouping (Figure 3)

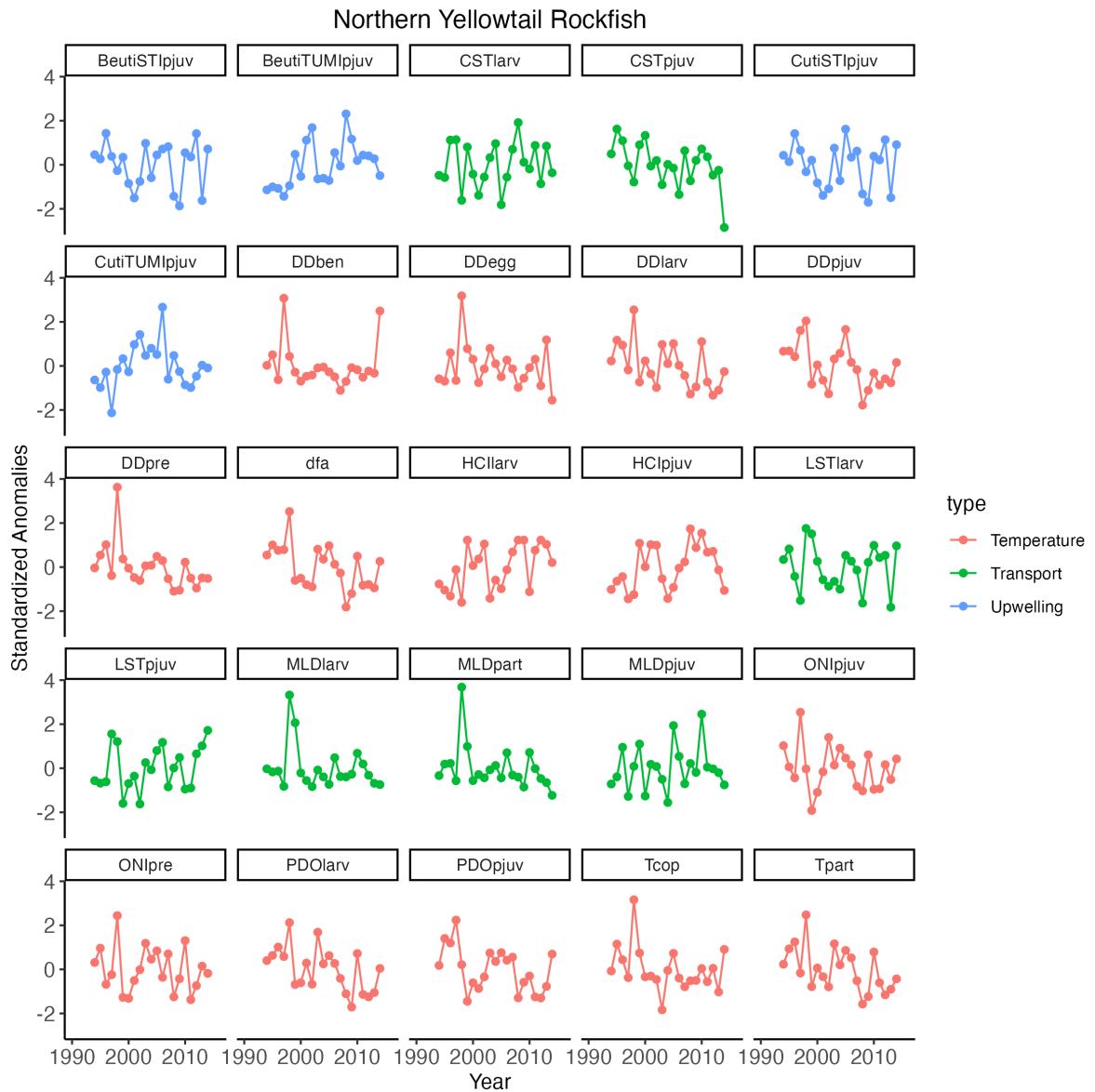


Figure 2: Time series of oceanographic conditions associated with northern Yellowtail rockfish recruitment

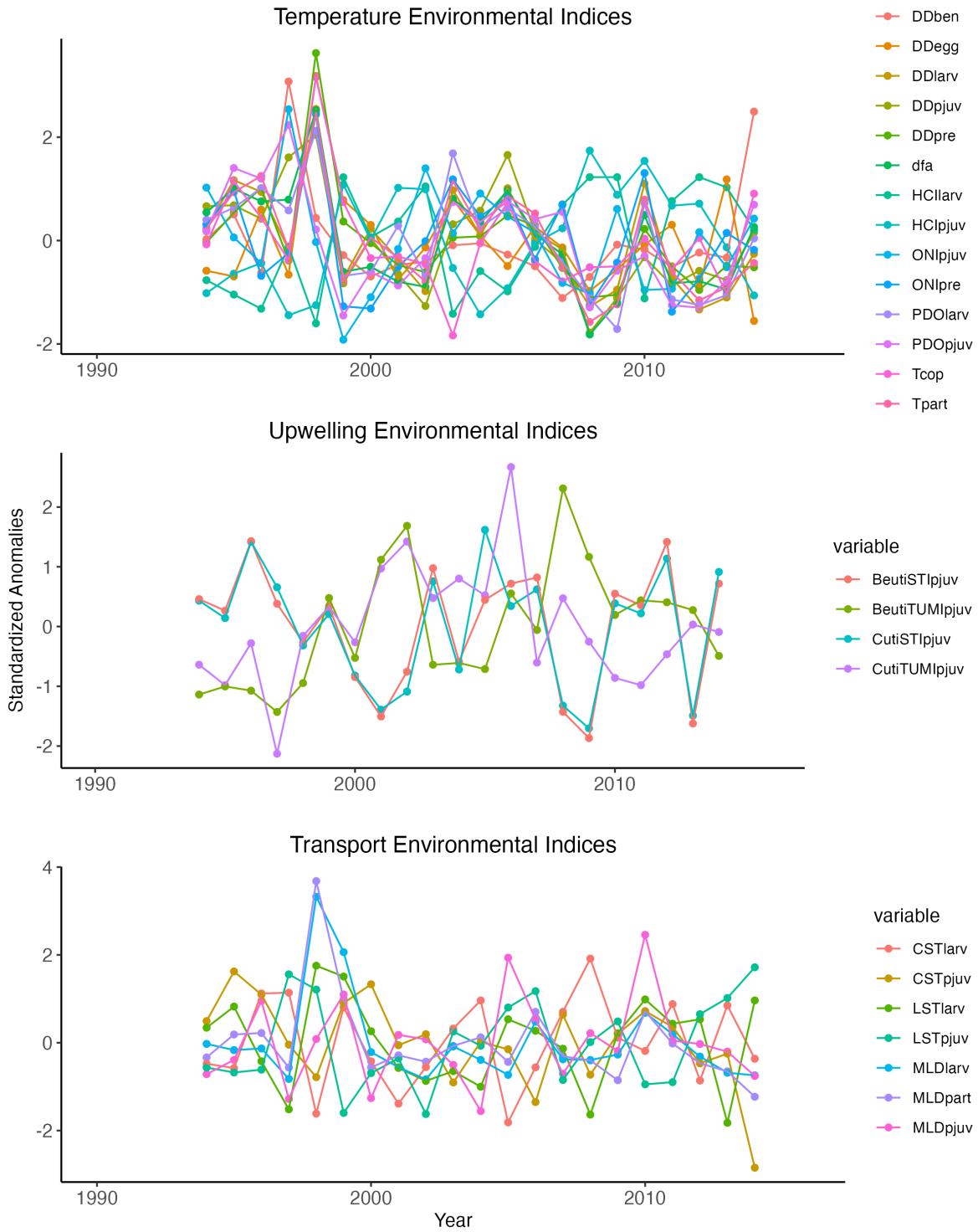


Figure 3: OceanographicTS2

Univariate Analysis

Univariate linear models and generalized additive models were used to understand the relative importance of single drivers for model fit and predictive capacity of oceanographic conditions on northern Yellowtail rockfish recruitment. We compared models with a single covariate using leave-one-out cross validation (LOO-CV) and leave-future-out cross validation (LFO-CV). We considered two ways of looking at LFO-CV, leaving the last 10 years of data out of the model and predicting one year ahead and leaving only the last 5 years of data out of the model and predicting one year ahead. Models were ranked based on the improvement of root mean square error (RMSE) relative to a model using year of observation as a predictor, such that the next year is predicted based on the previous year. The model fits and 5 and 10 years of prediction are plotted for linear models in Figure 28 and Figure 29 and for generalized additive models in Figure 30 and Figure 31.

For linear model approaches, we find that the improvement in RMSE depends on selection criteria used (Figure 4). When applying LOO-CV, only five oceanographic conditions improved RMSE relative to a year predictor. T_{cop} , MLD_{part} , MLD_{larv} , DD_{pre} , and $\text{CutiSTI}_{\text{pjuv}}^2$ were the top 5 oceanographic conditions for predicting recruitment ranging from 2.5% - 12.5% improvement in relative RMSE. 10-year LFO-CV had similar results, where MLD_{part} , MLD_{larv} , DD_{pre} , DD_{egg} , and $\text{CutiSTI}_{\text{pjuv}}^2$ were the top 5 predictors. Relative RMSE improvement was much higher using LFO-CV, where nearly all oceanographic conditions had better predictive capacity than a year-only model and relative RMSE improvement ranging from 9% - 26% among the top 5 best oceanographic conditions (Figure 4). 5-year LFO-CV had the highest improvement in RMSE relative to the year model, ranging from 68% - 80% improvement, but the best oceanographic predictors of recruitment were different than the 10-year LFO-CV and LOO-CV. The only condition that ranked in the top 5 for all selection criteria was DD_{pre} . T_{part} , PDO_{larv} , HCl_{larv} , and DD_{larv} were also ranked in the top 5 predictors using 10-year LFO-CV. This highlights the importance of temperature variables for predicting the last 5 years of data relative to transport or upwelling. Notably, the last 5 years of data in this analysis were 2009 - 2014, which encompasses the beginning of abnormally warm heatwave which began in December, 2013. The relative importance of temperature compared to other oceanographic conditions like settlement will be important to examine as new recruitment deviations become available.

For generalized additive models, the top supported oceanographic drivers were identical to the top oceanographic conditions for linear models by selection criteria, where the 5-year LFO-CV had more support for temperature conditions as predictors (Figure 5).

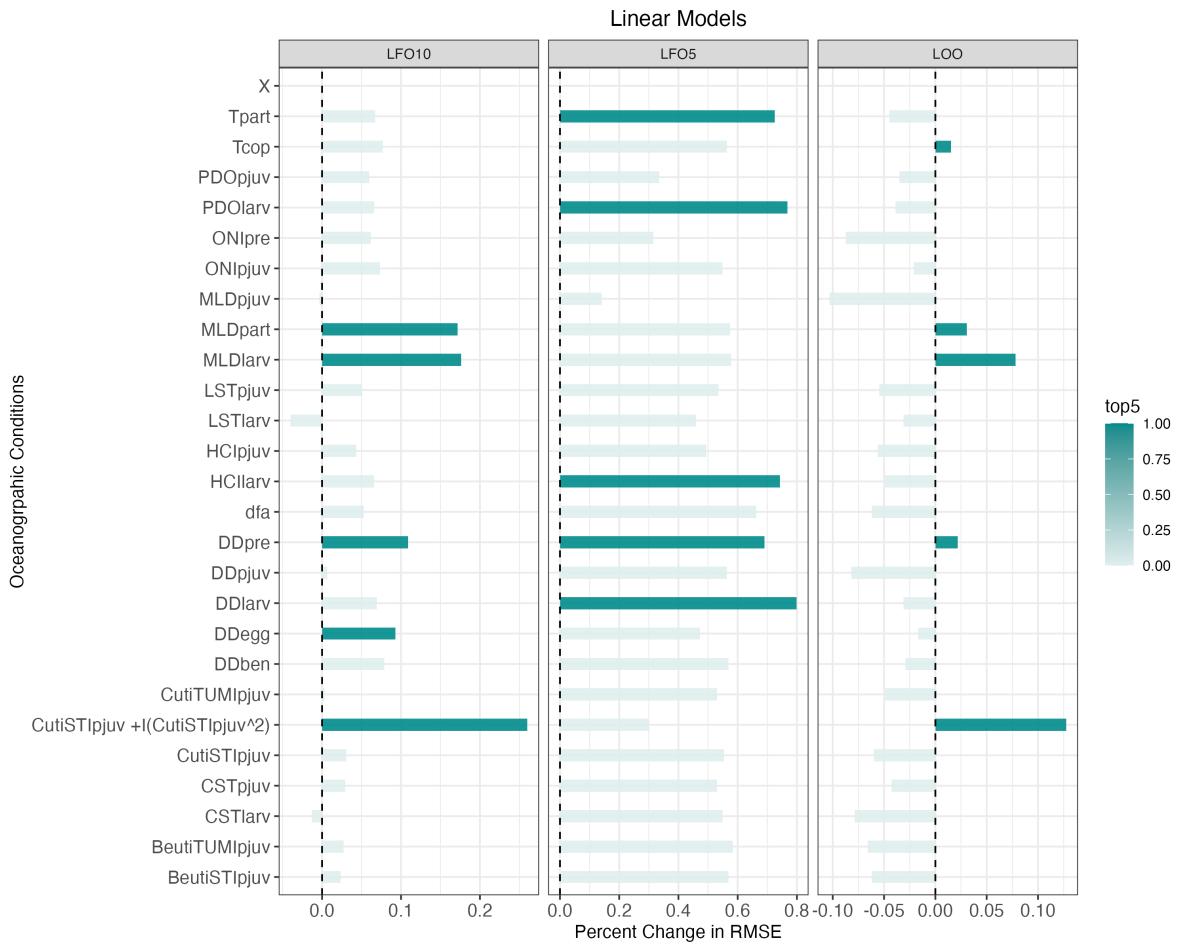


Figure 4: The top 5 ranked covariates for linear models using LOO-CV and LFO-CV predicting the last 5 and 10 years of data. RMSE improvement is relative to a using year only. Darker color indicates the top 5 ranked models

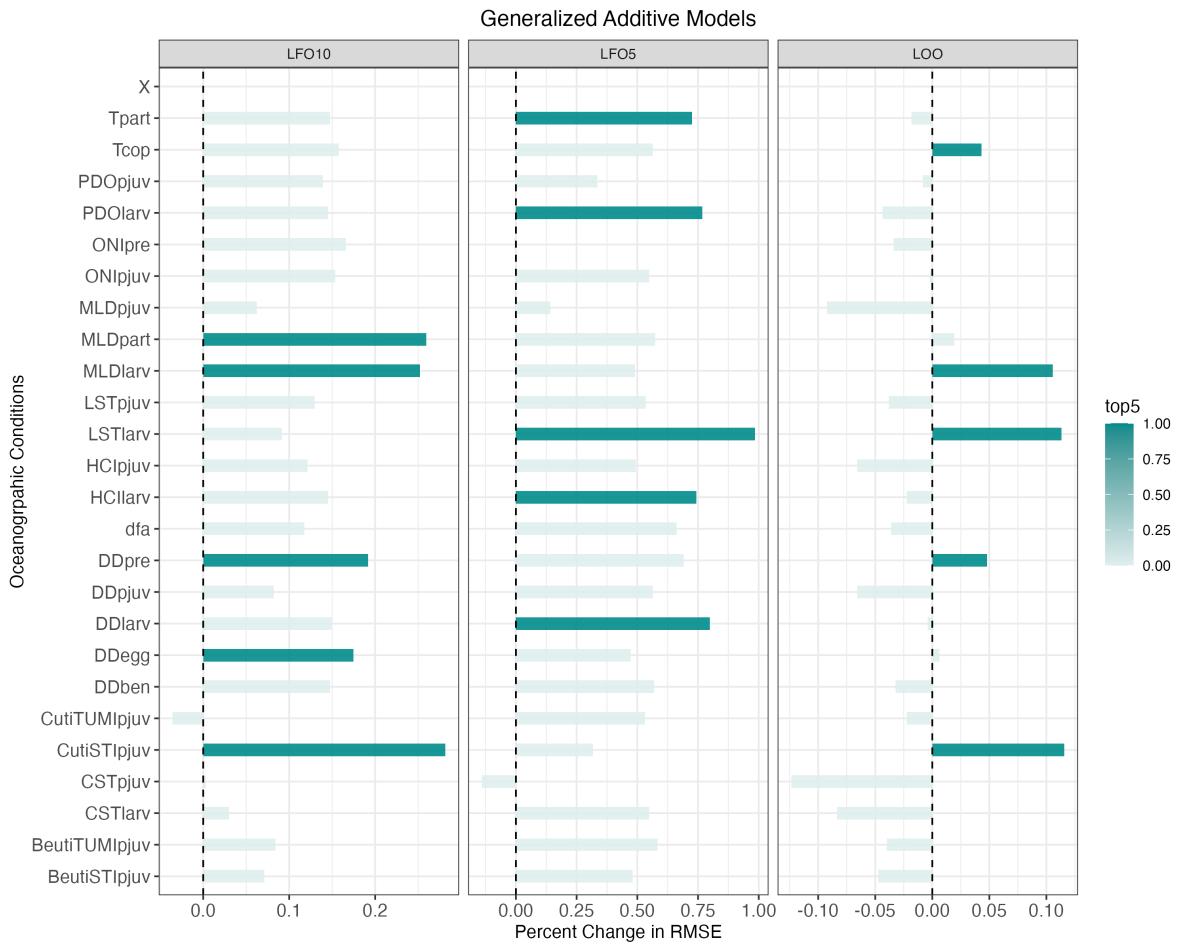


Figure 5: The top 5 ranked covariates for generalized additive models using LOO-CV and LFO-CV predicting the last 5 and 10 years of data. RMSE improvement is relative to a using year only. Darker color indicates the top 5 ranked models

Time-varying model selection

The differences in which covariates have the most support in univariate models indicates the relative strength of different oceanographic conditions to predict recruitment of northern Yellowtail rockfish likely varies through time. To further evaluate these time varying effects and the sensitivity of time series selection to the time period used, we used AIC weights with three approaches to evaluating the time-varying importance, 1) a 10-year rolling window, 2) forward addition of 1-year starting with first ten years of data (1993 - 2002) and 3) backwards addition of 1-year starting with the last ten years of data (2014 - 2005). We applied these approaches using generalized additive models.

The 10-year rolling window illustrates which variables improve model fit the most over different time periods. Figure 6 shows LST_{larv} and MLD_{larv} were important in the early time periods became less important in the middle time period, and more important in recent years. In contrast, ONI_{pre} was most important during the middle windows. MLD_{pjuv} became more important in the recent windows. Notably, AIC weight became more evenly distributed across oceanographic conditions for the most recent windows, with more AIC weight allocated to temperature variables.



Figure 6: AIC weight for each oceanographic variable for 10-year time periods between 1993 and 2014

The forward addition approach shows changes in the relative importance of oceanographic conditions for model fit that is informed by the earliest data in the time series. We find that CutiSTI_{pjuv} is supported with all windows, with particularly strong support with data from 1993 - 2006 (Figure 7). Once the full time series is included in the model selection process, CutiSTI_{pjuv} has weaker support in favor of more diffuse support for LST_{larv} (which also had strong support with the earliest window), MLD_{larv} and temperature variables.

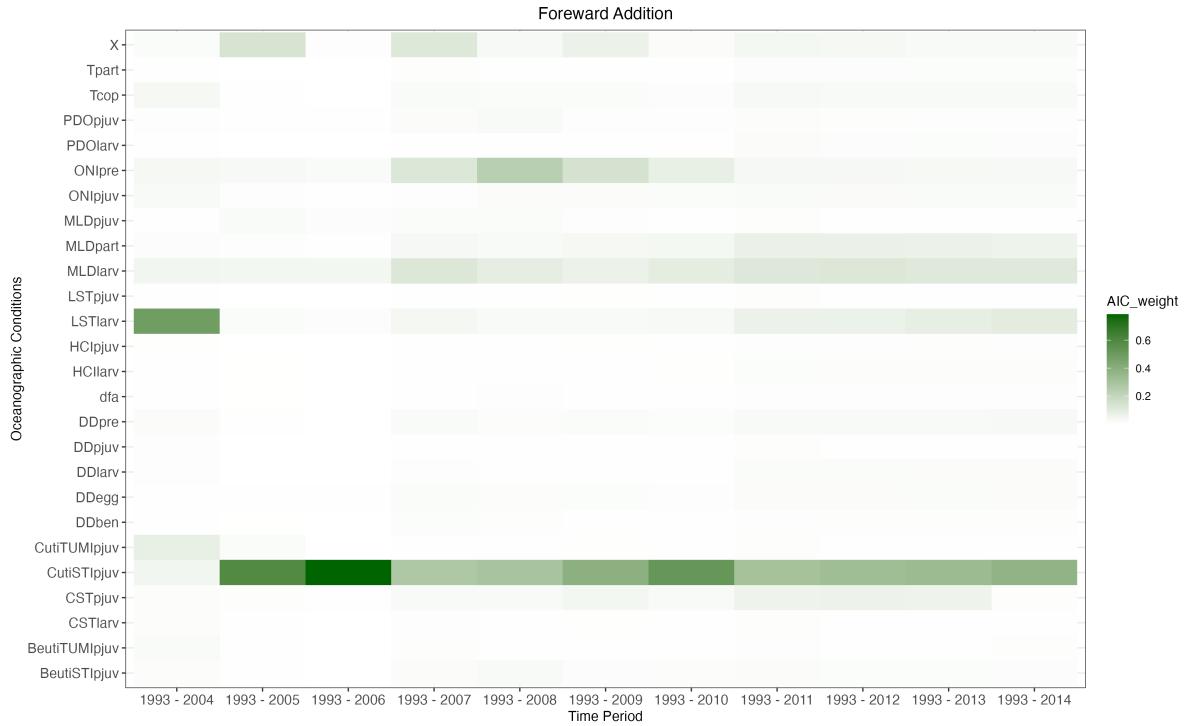


Figure 7: AIC weight for each oceanographic variable starting with the earliest 10 years (1993 - 2003) and iteratively adding one year of data to the model selection

Using the backwards addition approach helps us examine which data are most informative for recent time periods and how sensitive the selection is to extending the time period further back. Specifically, this analysis can be used to which predictors have the most support if we were only to use the most recent 10 or 15 years of data rather than the entire time period. We find LST_{larv}, and MLD variables have the greatest AIC weight in most recent years (Figure 8). As the time series is extended further back there is more support for CutiSTI_{pjuv}, which is expected based on the rolling window and forward selection processes.

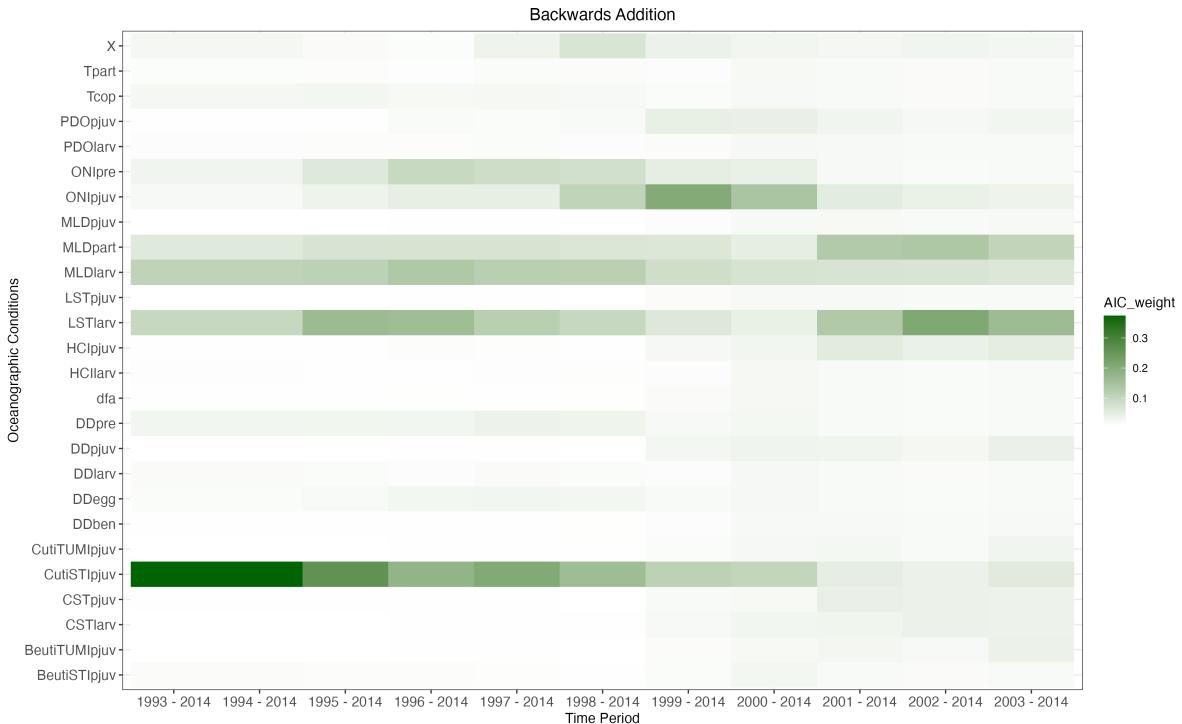


Figure 8: AIC weight for each oceanographic variable starting with the most recent 10 years (2004 - 2014) and iteratively adding one year of data to the model selection

Multivariate Analysis

Marginal Mean Improvement RMSE

After examining the fits and dynamics of univariate models, we examined the model fits and predictive capacity using the same cross validation techniques as the univariate approach. We calculated variable importance scores as the mean marginal improvement in RMSE for each cross validation technique. Marginal improvements in RMSE are dependent on both information in a predictor, as well as redundancy in information across predictors (e.g. if variable x and y are in a model, and z is highly correlated with x , adding z to a model will not improve RMSE). For any potential covariate considered in models with m predictors, we used the set of n models with $m - 1$ predictors that did not include that covariate as a baseline, and for each calculated the average relative change in RMSE. We fit all possible combinations of up to 3 covariates while excluding combinations that are highly correlated from being included in the same model.

We show the percent change in RMSE in Figure 9 for all covariates and for the top 5 models in Figure 10. In general, the best covariates had strong agreement using marginal mean improvement in RMSE in multivariate models as they did with AIC weights with univariate models and still varied with cross validation techniques.

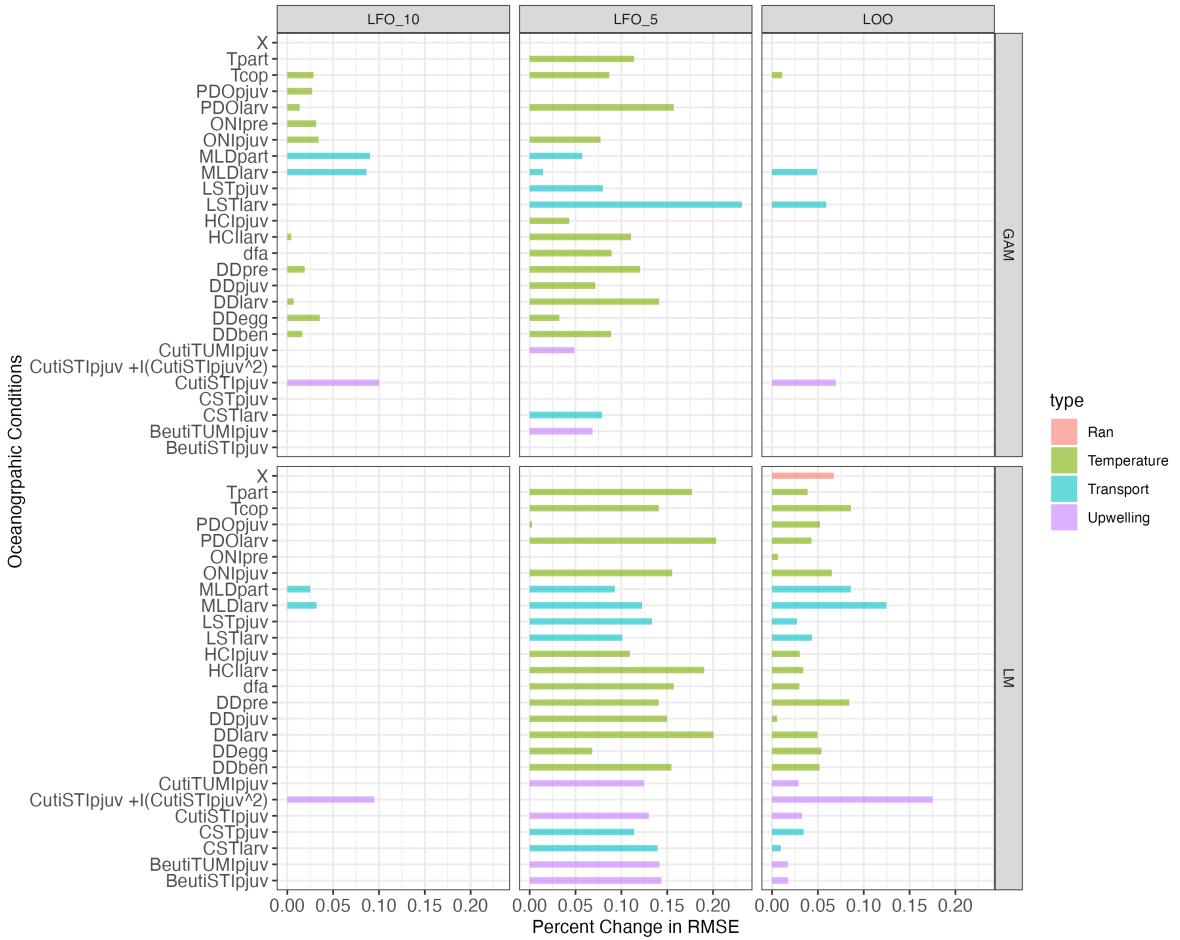


Figure 9: Marginal mean improvement in RMSE represented as the percent change in RMSE by adding in an specific oceanographic condition to the model



Figure 10: Top 5 oceanographic conditions for improving RMSE based on medle type and cross validation approach

Best Models with up to 3 covariates

The best models for each cross validation type (LFO-5, LFO-10, and LOO) and model type (LM or GAM) included some of the oceanographic conditions identified were identified as top performing conditions using marginal improvement of RMSE, but not all.

Linear Models

When applying LOO to linear models the top performing model included LST_{pjuv} , ONI_{pjuv} and $CutiSTI_{pjuv}$. This model had a R^2 value of 0.48 and all variance inflation factors were less than 2 (Figure 11). $CutiSTI_{pjuv}$ was the only variable that was ranked in the top 5 based on marginal improvement of RMSE for LOO of LMs.

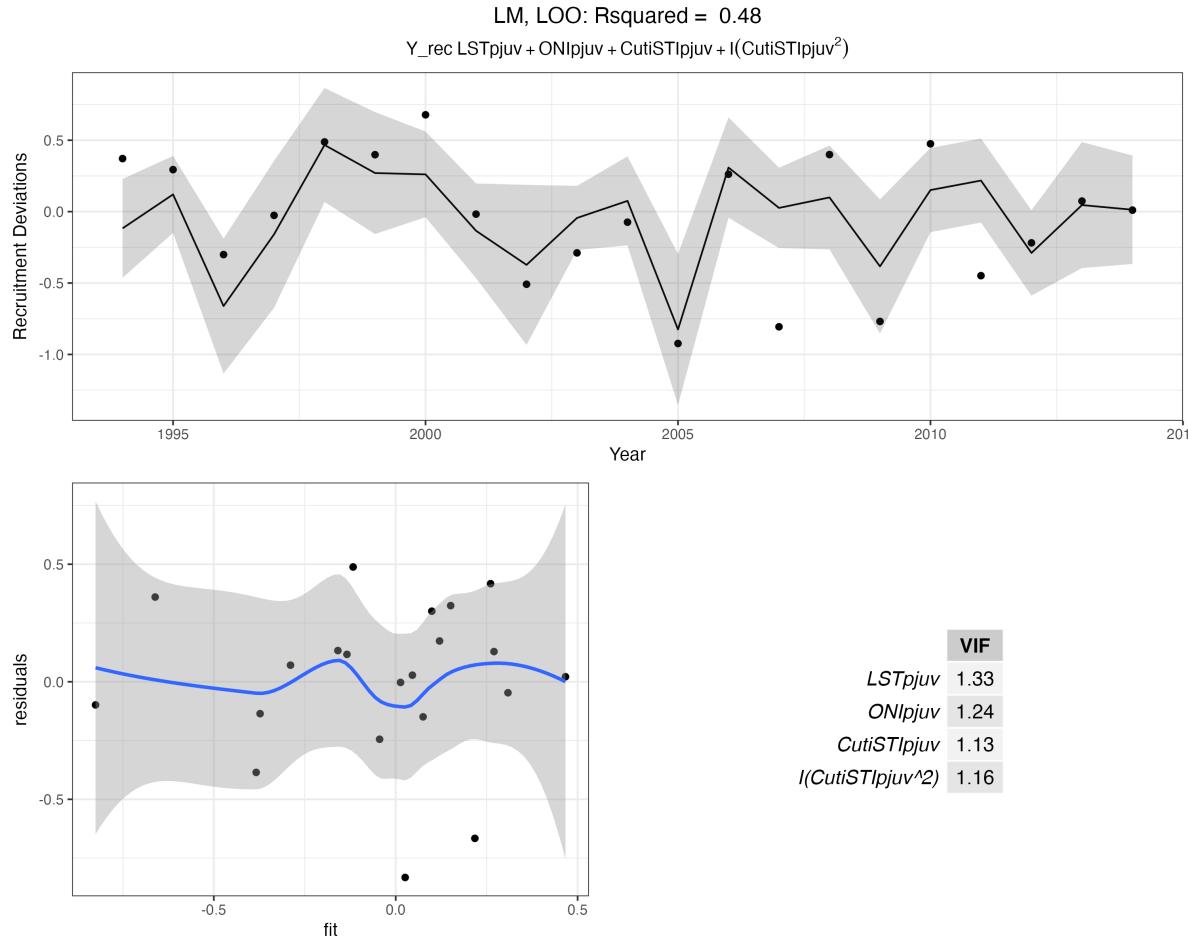


Figure 11: Best performing linear model using LOO

When applying LFO-5 to linear models the top performing model included DD_{ben} , DD_{pre} and HCI_{pjuv} (Figure 12). This model had a R^2 value of 0.20 and all variance inflation factors were less than 2. Notably DD_{ben} was not supported based on marginal improvement of RMSE, but it was included in each of the top 5 LMs using LFO-5. Most models with strong support using LFO-5 suffered poor model fits to the data. This may be unimportant if short term predictive capacity is the most important criteria, but may not make a compelling case for an index.

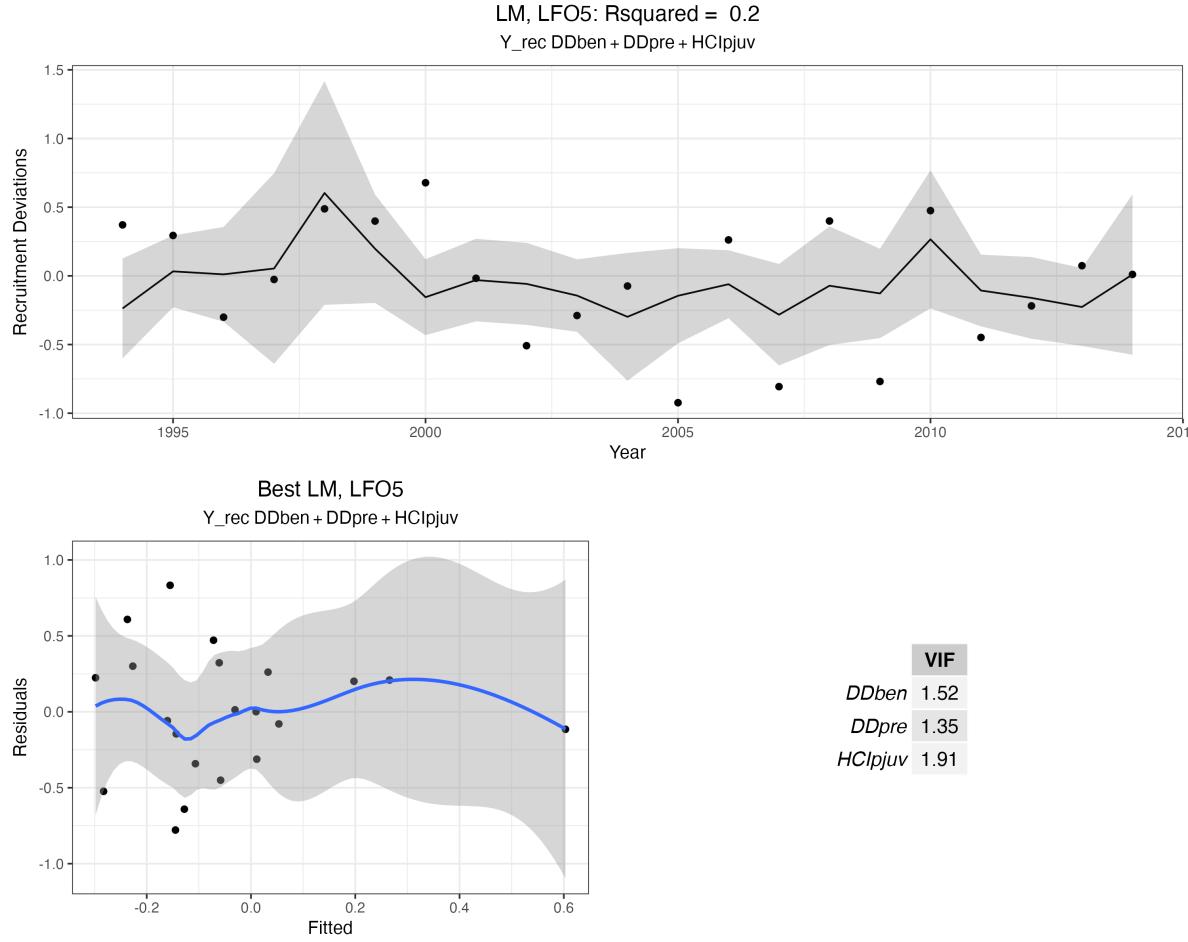


Figure 12: Best performing linear model using LFO-5

When applying LFO-10 to linear models the top performing model included MLD_{pjuv} , LST_{pjuv} , and $CUTIsti_{pjuv}$ (Figure 13). This model had a R^2 value of 0.4 and all variance inflation factors were less than 2. Notably, MLD_{pjuv} did not have much support based on marginal RMSE improvement for any model (LM or GAM) or cross validation technique.

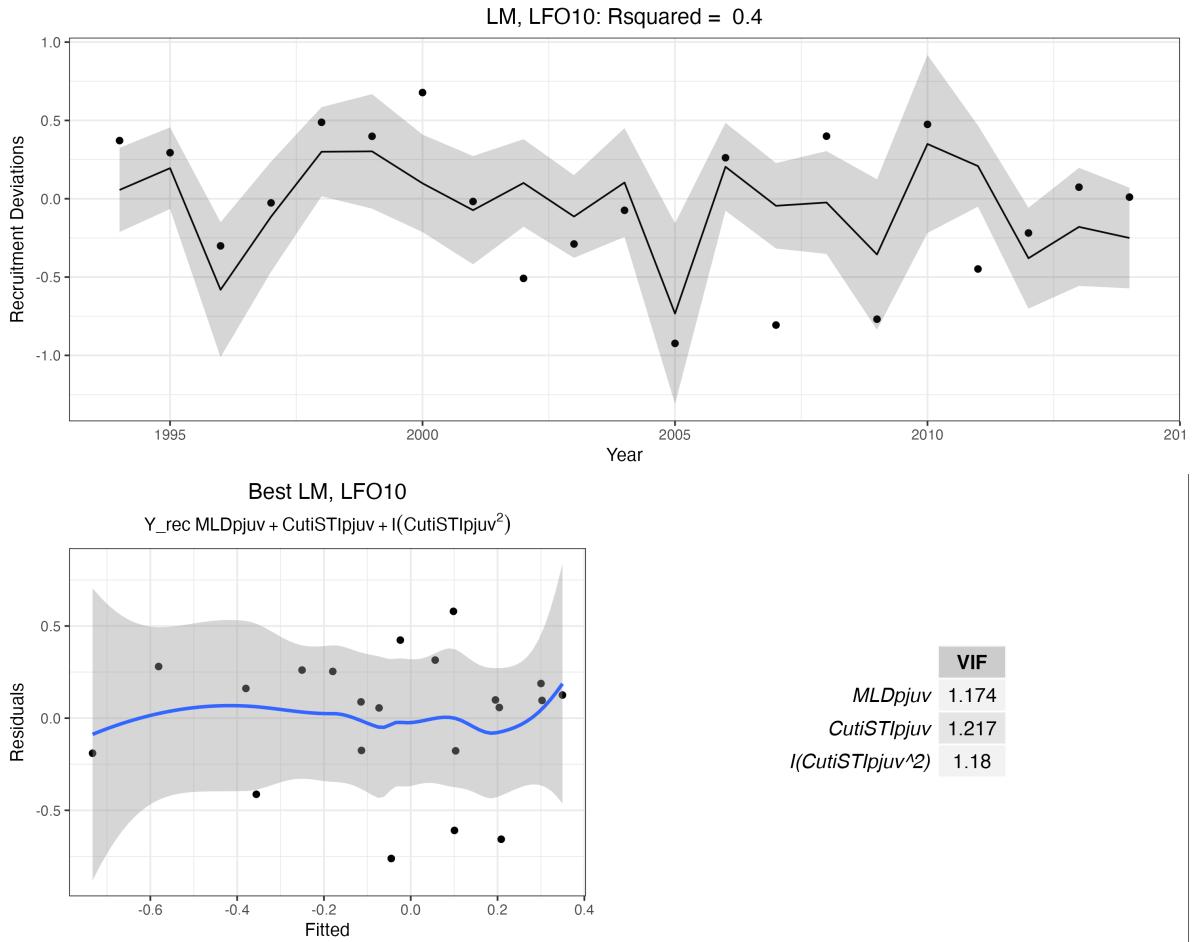


Figure 13: Best performing linear model using LFO-10

Generalized Additive Models

When applying LOO to GAMs the top performing model included HCI_{larv} , PDO_{pjuv} and LST_{larv} . This model explained 56% of the deviance and all variance inflation factors were less than 3 (Figure 11). Only LST_{larv} was ranked in the top 5 based on marginal improvement of RMSE for LOO of GAMs.

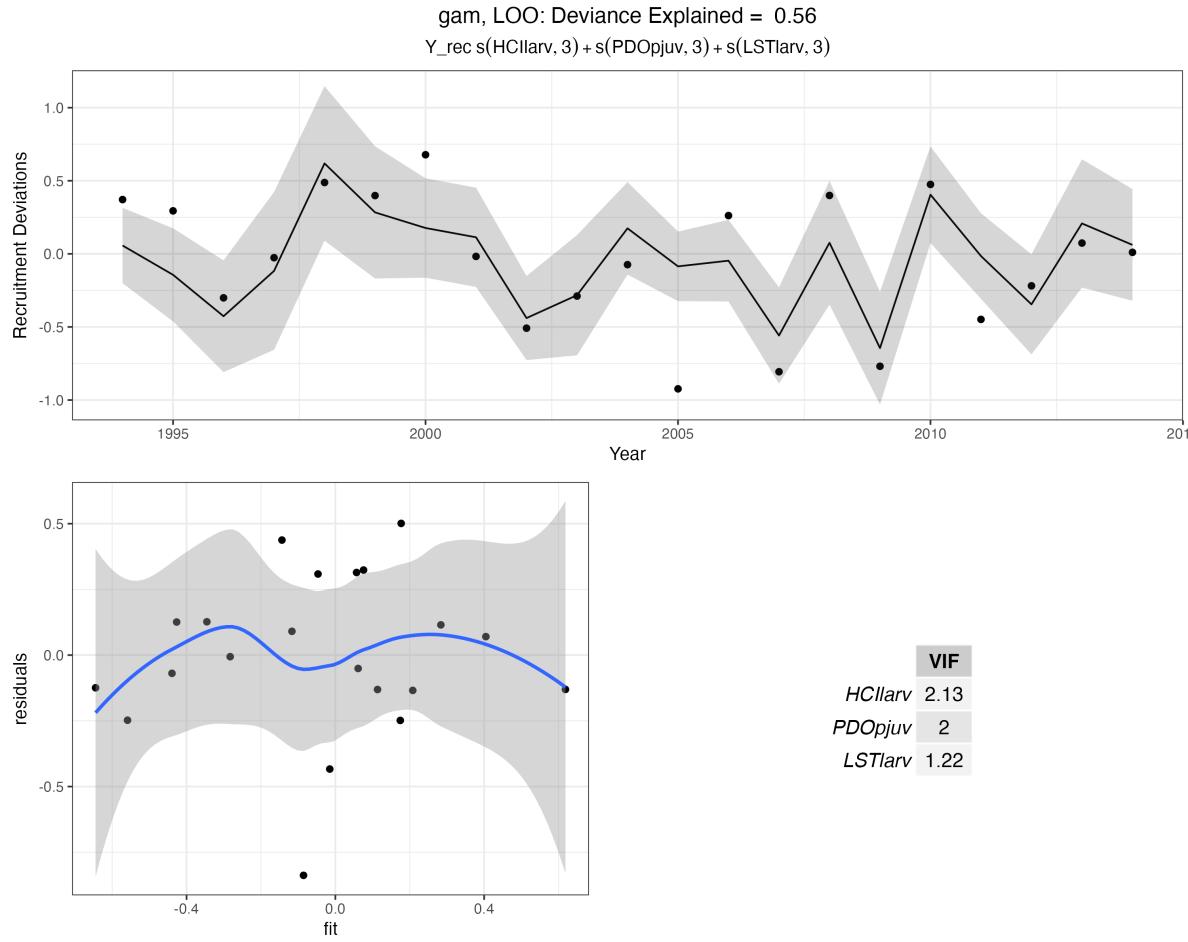


Figure 14: Best performing GAM using LOO

When applying LFO-5 to GAMs the top performing model included HCI_{pjuv} , T_{part} and LST_{larv} . This model explained 38% of the deviance and all variance inflation factors were less than 3 (Figure 15). Both T_{part} and LST_{larv} were ranked in the top 5 variables based on marginal mean RMSE improvement in GAMs using LFO-5.

When applying LFO-5 to GAMs the top performing model included $CUTIsti_{pjuv}$, and MLD_{pjuv} . This model explained 37% of the deviance and all variance inflation factors were less than 3

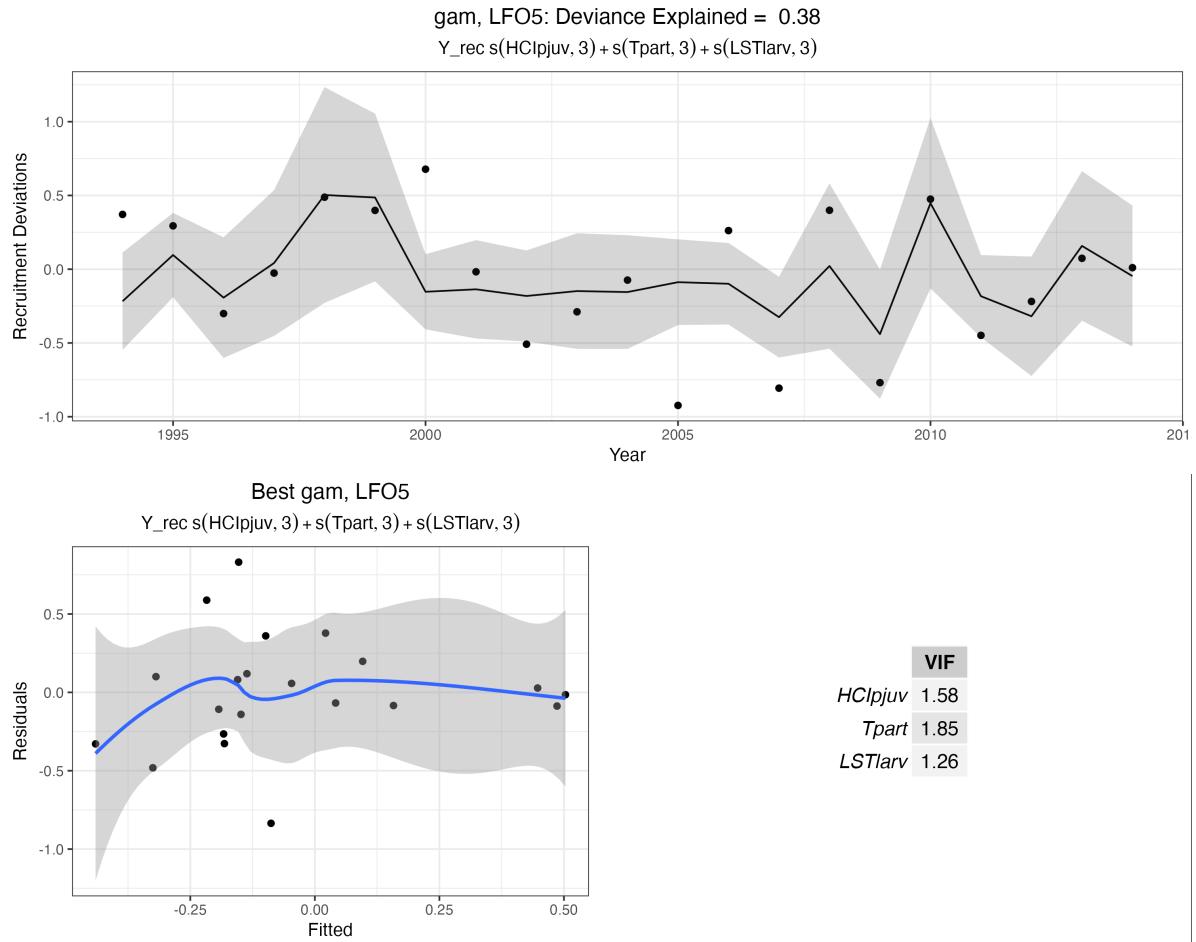


Figure 15: Best performing GAM using LFO-5

(Figure 16). CUTI sti_{pjuv} was ranked in the top 5 variables based on marginal improvement of RMSE.

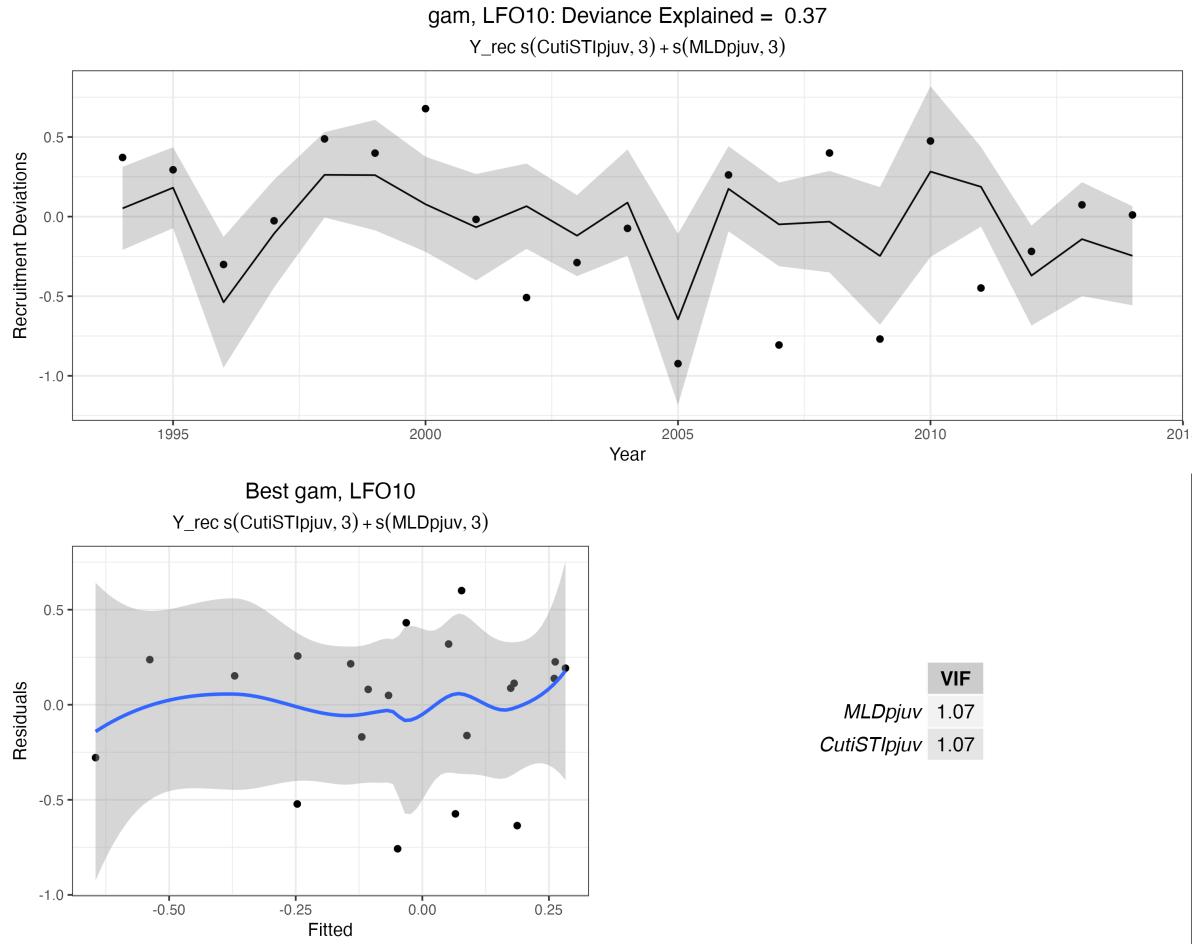


Figure 16: Best performing GAM using LFO-10

Best model using strongest predictors

Using a single best model is not always an ideal approach, as selecting a single best model between large numbers of models often means relatively arbitrary improvements in predictive capacity and/or fit relative to other highly ranked models. We also limited the combinations to three covariates to avoid overfitting but more than four covariates could be included with appropriate tests of multicollinearity. We fit two models, an LM and a GAM, using the best predictors based on the total weight of evidence described above. These variables were: ONI_{pre} which impacted model fit particularly between 1998 - 2008; CutiSTI_{pjuv} which was particularly important in the early time periods and had strong support as a best performing covariate using LOO and LFO-10, LST_{larv} which had particularly strong support using LFO-5, MLD_{part} which had strong support using both LOO and LFO-10.

This model construction is a qualitative selection process (support by the quantitative metrics described above) to balance which oceanographic conditions have the most support based on cross validation techniques in addition to the sensitivity of predictor selection to the time period used. An alternative approach could be to use a backwards selection approach with VIFs (which I did test and it provided similar results).

For the best models, I selected: 1. HCl_{larv} which was an important predictor using time windows in the middle of the time period (Figure 7, Figure 8, Figure 6). Other temperature variables could be considered, such as DD_{larv} or PDO_{larv}. Alternatively ONI_{pre} could be used which was particularly important to the fit from 2017- 2010 (see alternative best model below). 2. CutiSTI_{pjuv} which was the highest ranked oceanographic condition using LFO-10 and LOO for both univariate and multivariate approaches and greatly influenced model fit when the years 1993 - 2000 were included in the time series 3. MLD_{larv} which was particularly important for model fit when the years 2004 - 2014 were included in the time series (Figure 6) and was highly ranked for LOO and LFO-10 (Figure 10). 4. HCl_{larv} which was highly ranked for LFO-5, which exclusively supported oceanographic variables describing temperature (Figure 10). Other temperature variables were explored and provided similar model performance.

Before we fit models, let's look at the shape of these relationships.

Fitting a model with the best oceanographic conditions described above using an LM had an R² of 0.53 and VIFs less than 3 and a reasonable distribution of residuals (Figure 18).

To further investigate we can look at the diagnostic plots. These results are not overly concerning, but there are a few years that seem to have disproportionate influence, particularly 1996 (3), 2007 (14) and 2008 (15). These years and their influence on the model may explain some of the temporal variability in best predictors.

To further understand the performance and sensitivity of this model we can look at its ability to predict the last 5 years of data. The approach for this may vary by species or availability of predictions of environmental data. Here, I omitted the most recent 5 years (2009 - 2014) of recruitment data and provided the most recent 5 years of environmental data. 1-2 years may

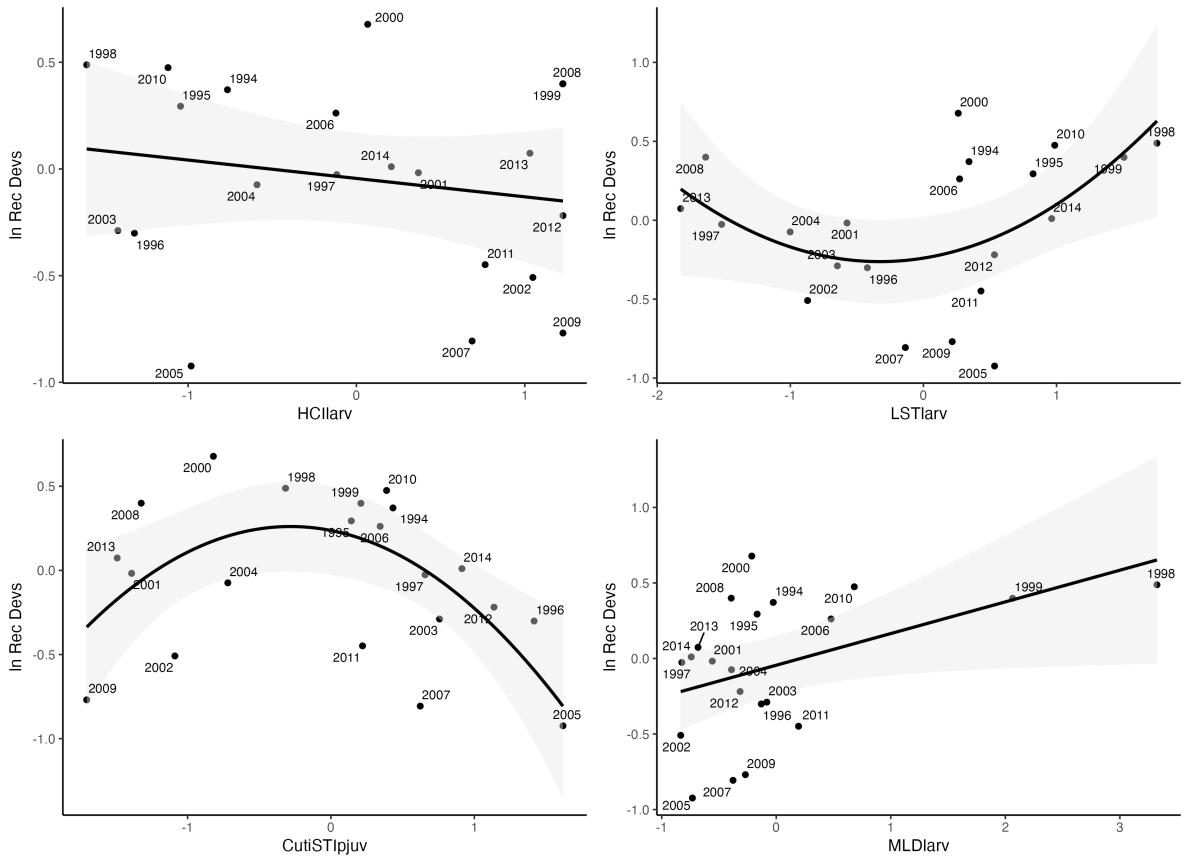


Figure 17: Shape of relationship between recruitment deviations and oceanographic conditions in the best lm model

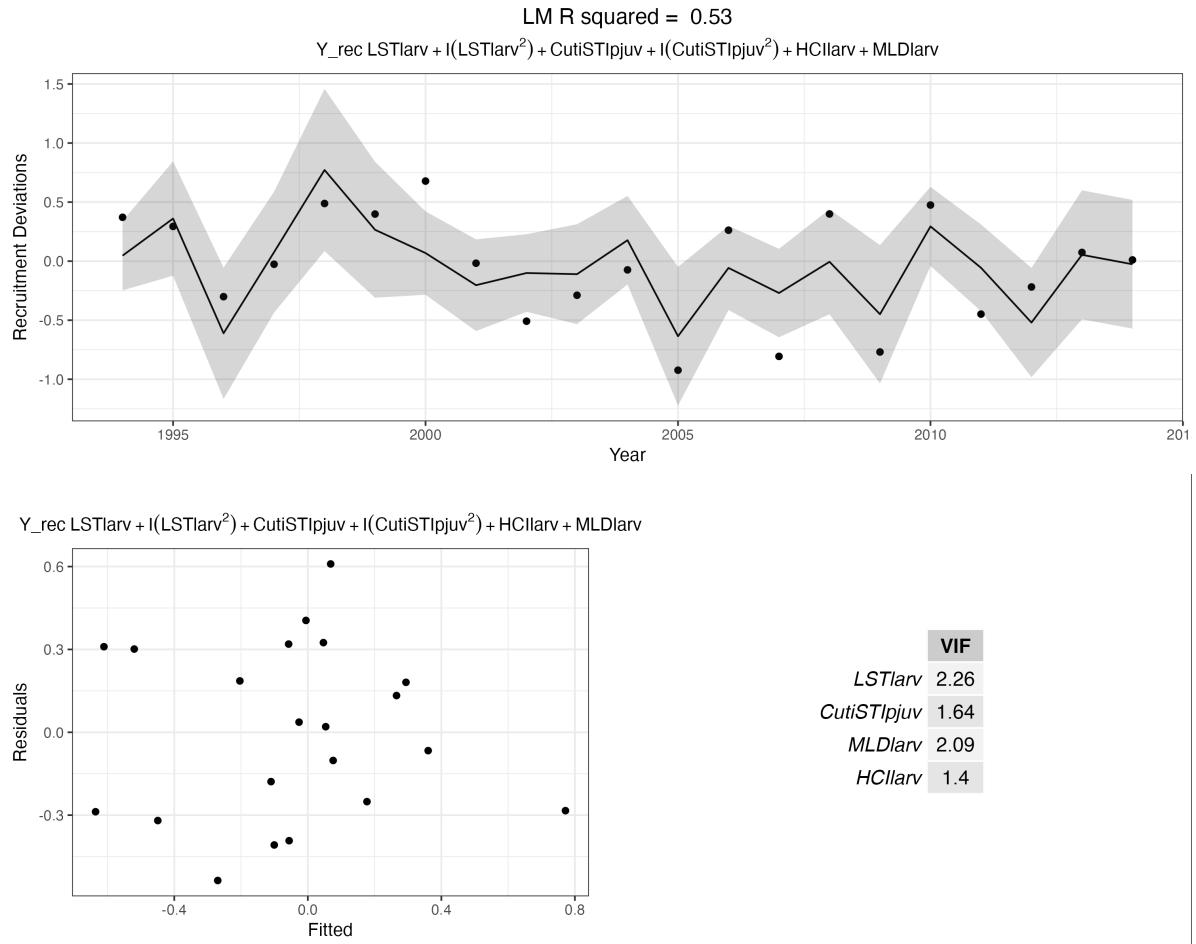


Figure 18: Best performing LM constructed using a qualitative weight-of-evidence approach

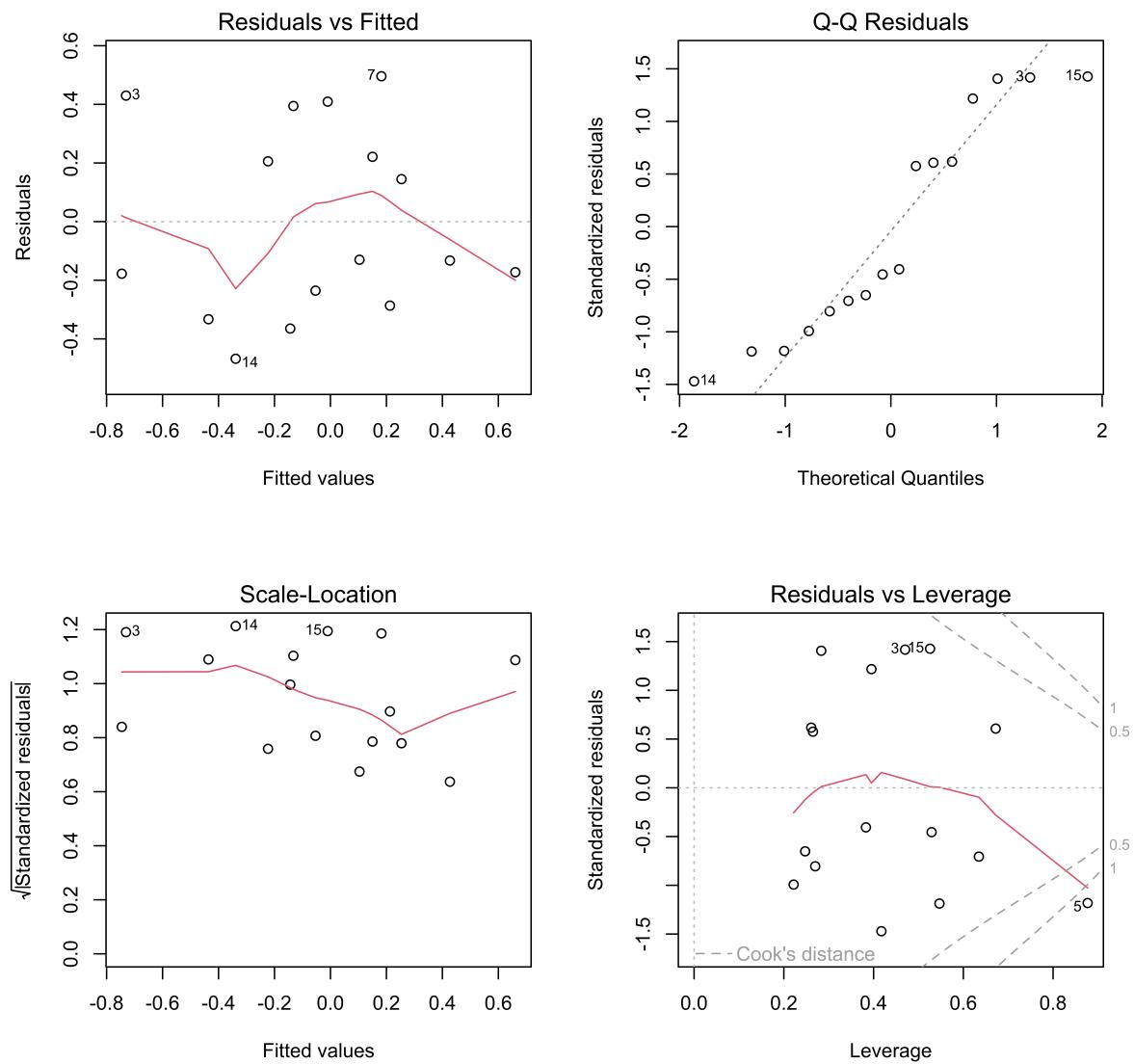


Figure 19: Diagnostic plots for the best performing LM

be more useful for sablefish or hake and may also be a more realistic window of predictions available from MOM6.

The model performs quite well (Figure 20) in predicting recruitment and also capturing the overall pattern in the last 5 years of data.

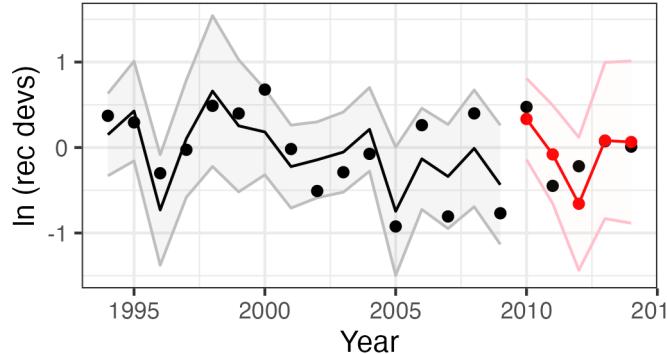


Figure 20: Model fit of the best performing LM to recruitment deviations (black) relative to

A quick investigation into the best performing model that was selected using LFO-5 shows that the weight-of-evidence approach for generating the model does better than choosing the single best performing model for a single criteria, even when that criteria (LFO-5) is specific to the model performance you are interested in (here, predicting the last 5 years) (Figure 21).

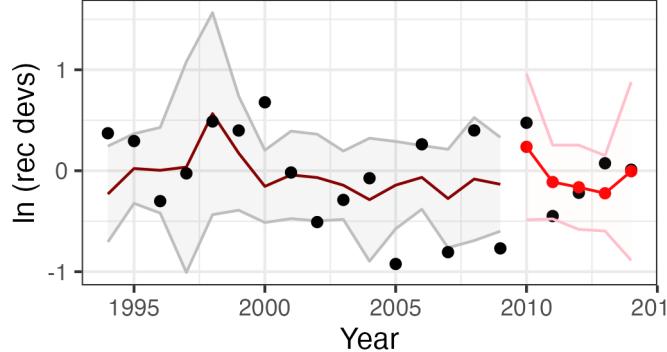


Figure 21: Model fit of the best performing model with LFO-5 for an LM to recruitment deviations (black) relative to

We can also look at the shape of these relationships to understand patterns through time and whether they align with our hypotheses. The relationship with HCI_{larv} is quite weak, which is expected given it was not a strongly supported oceanographic condition using the univariate approach. Similarly, we find a strong non-linear relationship with $CutiSTI_{\text{pjuv}}$ that aligns with our univariate results. LST_{larv} shows an interesting relationship that reflects a threshold

relationship (note: the model still performs quite well with LST as a linear predictor). This relationship mystified me for quite a while, until I realized 2005 and 2009 are the years with highest and lowest upwelling which may explain the conflicting responses of years with average LST_{larv} . In years with average LST_{larv} , other oceanographic conditions are likely to exert a higher influence on recruitment. The two anomalously above average years of MLD_{larv} are important, notably 1998 was also identified as a potential leverage year, potentially due to the anomalous MLD conditions. Notably, MLD_{larv} still has a positive relationship when these years are omitted from the model.

Now, let's investigate the GAM model. We expect this model to perform quite similarly to the lm model. This model explained 65% of the deviance and had VIFs less than 3 and a reasonable distribution of residuals (Figure 22).

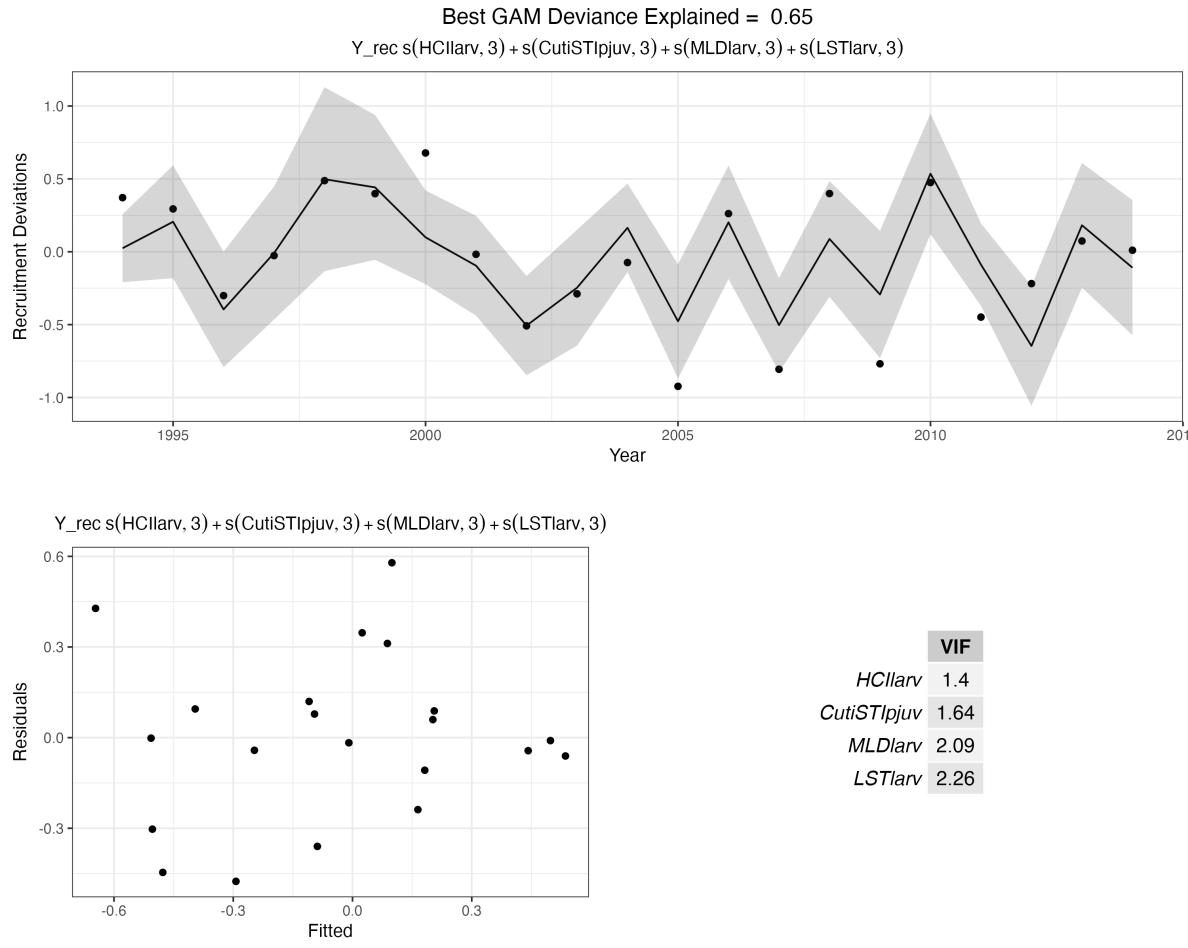


Figure 22: Best performing GAM constructed using a qualitative weight-of-evidence approach

We can look at the same diagnostics (Figure 23) and see that 2012 and 2009 are also potential leverage years (Figure 24 see orange points).

Similar to the linear model, this model does an excellent job predicting the last 5 years of recruitment particularly the trends (@gam5pred) with the exception of 2012 which the model drastically underpredicts. Looking at the partial effects of the oceanographic conditions relative to the relationships, we do see that LST_{larv} does look more like a threshold effect with a more flexible model. NOTE: explorations using MLD_{part} instead of MLD_{larv} does result in a better prediction of 2012 but only explains 53% of the deviance.

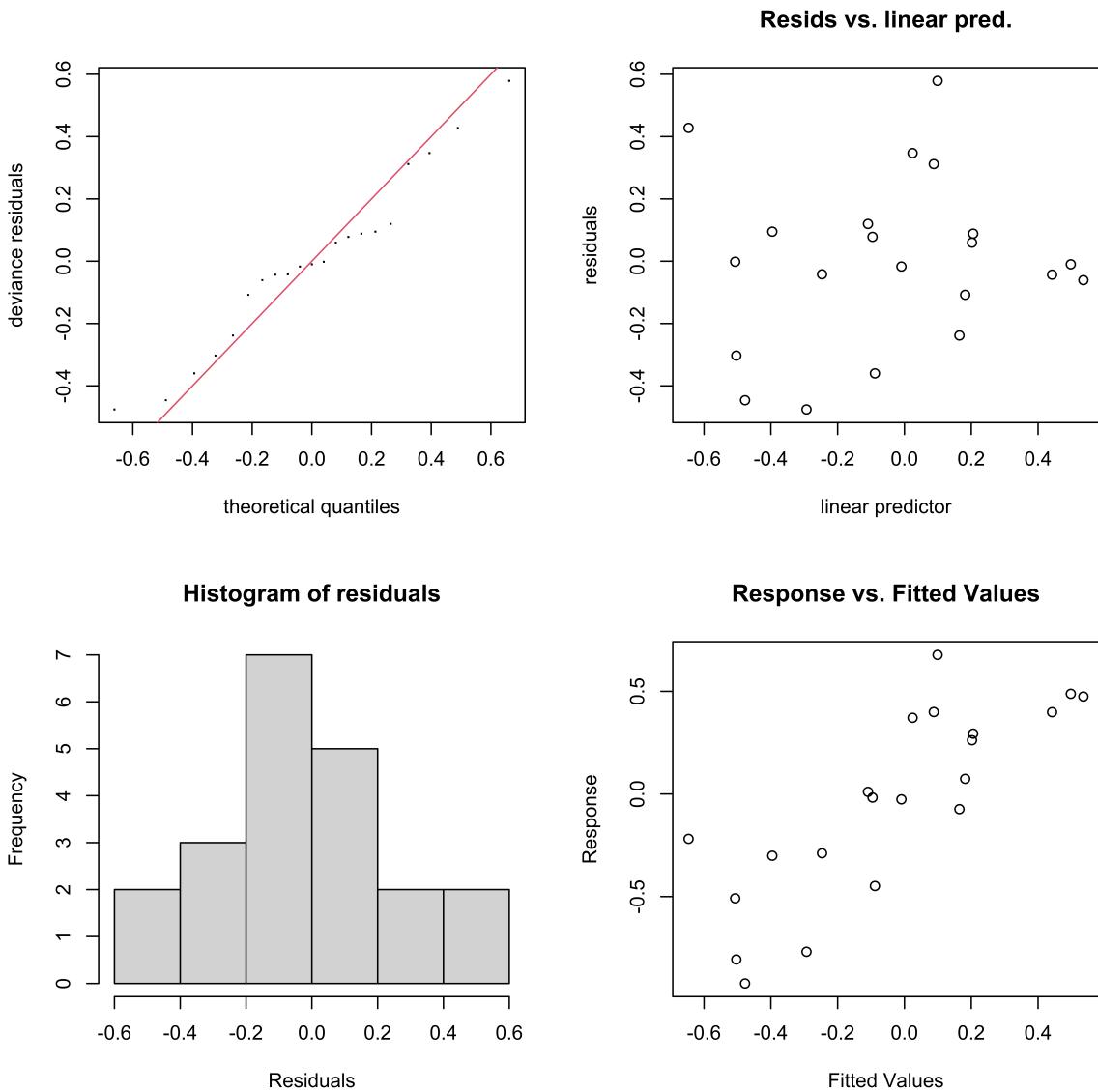


Figure 23: Best GAM model diagnostics

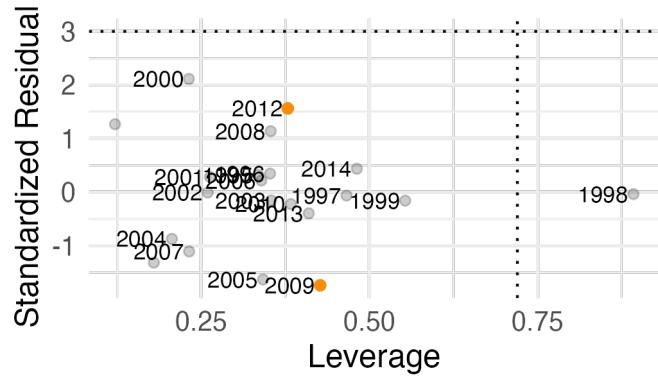


Figure 24: Best GAM model leverage diagnostics

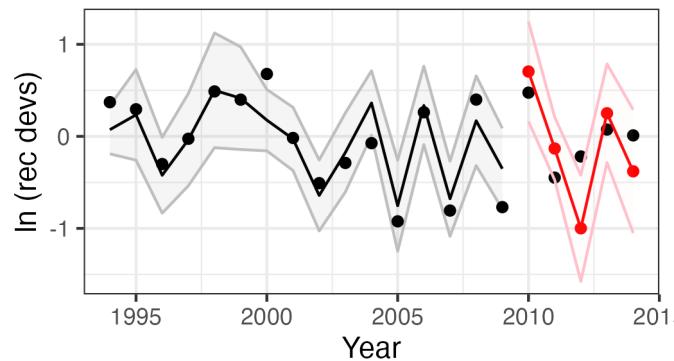


Figure 25: Model fit of the best performing LM to recruitment deviations (black) relative to $\ln(\text{rec devs})$ over time

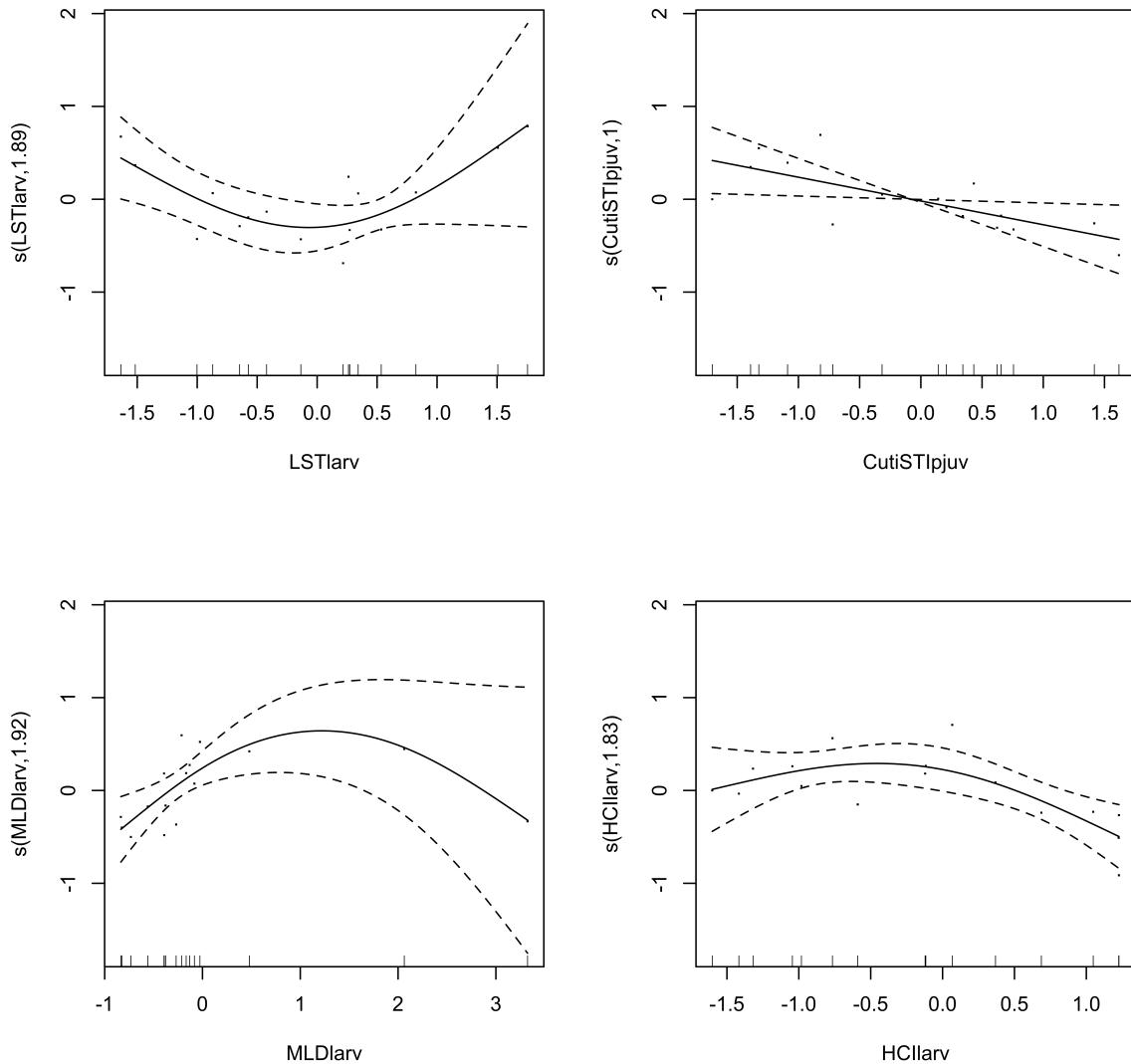


Figure 26: Partial effects of each oceanographic condition for the best GAM. Points denote residuals

Non-stationary Models

The last investigation was testing time-varying GAMs where the smoothed effect is able to vary by year such that year is essentially treated as a random effect. In short, mean improvement of RMSE decreased with additional predictors (Figure 27). I suspect this a bit due to how I performed the comparison, I did the same multivariate approach described above but every oceanographic condition was added into the comparisons as a time-varying response. A more careful consideration of comparing these models to their stationary counterpart may be more valuable (which I did do in a disorganized exploration as well). So, for many combinations, there were multiple time-varying responses in a single model which I suspect is prone to overfitting - however we do not have strong evidence supporting a non-stationary relationship necessary to select which variables should be time-varying and which shouldn't. I also am not sure we have justifiable motivations for fitting time varying relationships, and the evidence for variability through time could be equally justified with non-linear relationships or red noise in short time series. This may be worthwhile to further explore in the multi-species paper, or even on its own, but I do not think it is a priority for the 2025 assessment.



Figure 27: Model fit of the best performing GAM to recruitment deviations (black) relative to

Conclusions

- we need multiple predictors, single predictors will not fit the TS or predict very well
- oceanographic conditions need to be continuously updated and re-evaluated. Well established relationships can decay through time. Different variables are supported in different time periods. Can we socialize the council to expect these predictors will not always be the same? Importance of temps since MHW years is a great example
- Exclusively picking a driver based on only the most recent data and/or only predictive capacity makes sense in some ways, but the complete lack of model fit for some of these make it hard to justify. A weight of evidence approach, that both considers variables important to LFO-5 and important to fit, might be a better process than purely dredging models, as illustrated in the positive performance of the best models described above.
- The role of temperature seems to be recently important based on LFO-5 results and rolling window analyses. Swapping out highly correlated temperature indices has a relatively negligible impact on the model performance or predicting the last 5 years of data. When multiple variables are well supported, represent similar things (or temporally autocorrelated conditons) the most interpretable or easy to communicate variable is likely the best option. One example, DD_{larv} could easily be swapped for HCl_{larv} for similar performance.
- which...all this means that the model may be very different with updated time series, and begs a question, how can we socialize to the council and others that we expect environmental indices to change through time, especially on decadal scales?

Table 1: Oceanographic Conditions

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
Precondition	Jul (Year 0) - Mar (Year 1)	90 - 180 m	(H1) Higher temperature (degree days) increases food demand, resulting in lower egg production, ultimately resulting in lower recruitment. (H2) El Niño/La Niña cause shifts in temperature and precipitation which lead to changes in recruitment success.	DDpre ONIpre	Degree days Ocean Niño Index	GLORYS Leising et al. (2024)

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
Copulation	Aug - Oct	90 - 180 m	(H3) Temperature may act as a spawning cue for initiation of copulation.	Tcop	Temperature	GLORYS
Egg fertilization	Nov - Dec	90 - 180 m	(H4) Higher temperature (degree days) affects delayed fertilization and development of the embryo.	DDegg	Degree days	GLORYS
Parturition	Jan - Apr (peak in Feb)	0 - 180 m	(H5) Temperature may act as a cue for birth of live larvae. (H6) Location of mixed layer depth may limit where in the water column mothers give birth.	Tpart MLDpart	Temperature Location of mixed layer depth	GLORYS
Larvae	Feb - Mar	0 - 90 m	(H7) Growth/predation hypothesis: Growth rate is faster in warmer water, leading to reduced time vulnerable to predators. (H8) Cross-shelf transport to settlement habitat affects recruitment. (H9) Long-shore transport to settlement habitat affects recruitment.	DDlarv CSTlarv LSTlarv	Degree days Net cross-shelf transport Net long-shore transport	GLORYS

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
			(H10) Location of mixed layer depth may limit where they are able to move in the water column, affecting transport and recruitment.	MLDlarp	Location of mixed layer depth	GLORYS
			(H11) The presence of cool upwelled waters in the surface mixed-layer affects the availability of nutrients and food for growth.	HCIIlarp	Habitat Compression Index	Leising et al. (2024)
			(H12) El Niño/La Niña cause shifts in temperature and precipitation which lead to changes in recruitment success.	ONIIlarp	Ocean Niño Index	Leising et al. (2024)
			(H13) Changes in wind speed and direction impact upwelling/downwelling processes, ultimately impacting recruitment.	PDOlarp	Pacific Decadal Oscillation	Leising et al. (2024)
Pelagic juvenile	Apr - Aug	30 - 130 m	(H14) Growth/predation hypothesis: Growth rate is faster in warmer water, leading to reduced time vulnerable to predators.	DDpjuv	Degree days	GLORYS
			(H15) Cross-shelf transport to settlement habitat affects recruitment.	CSTpjuv	Net cross-shelf transport	GLORYS

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
			(H16) Long-shore transport to settlement habitat affects recruitment.	LSTpjuv	Net long-shore transport	GLORYS
			(H17) Location of mixed layer depth may limit where they able to move in the water column, affecting transport and recruitment.	MLDpjuv	Location of mixed layer depth	GLORYS
			(H18) Food availability impacts growth and survival.	ZOOpjuv	Zooplankton availability	Leising et al. (2024)
			(H19) The presence of cool upwelled waters in the surface mixed-layer affects the availability of nutrients and food for growth.	HCIpjuv	Habitat Compression Index	Leising et al. (2024)
			(H20) El Niño/La Niña cause shifts in temeprature and precipitation which lead to changes in recruitment success.	ONIpjuv	Ocean Niño Index	Leising et al. (2024)
			(H21) Changes in wind speed and direction impact upwelling/downwelling processes, ultimately impacting recruitment.	PDOpjuv	Pacific Decadal Oscillation	Leising et al. (2024)
			(H22) Coastal upwelling impacts nutrient and food availability which contributes to growth and survival.	CutiSTIpjuv	Coastal Upwelling Transport Index	Jorgensen et al. (2024)

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
			(H23) Coastal upwelling impacts nutrient and food availability which contributes to growth and survival.	CutiTUMIpj	Coastal Upwelling Transport Index	Jorgensen et al. (2024)
			(H24) Nitrate is essential for primary productivity, impacting presence of phytoplankton available as a food source.	BeutiSTIpjuv	Biological Effective Upwelling Transport Index	Jorgensen et al. (2024)
			(H25) Nitrate is essential for primary productivity, impacting presence of phytoplankton available as a food source.	BeutiTUMIp	Biological Effective Upwelling Transport Index	Jorgensen et al. (2024)
Benthic juvenile	Sept - Dec	180 - 549 m	(H26) Growth/predation hypothesis: Growth rate is faster in warmer water, leading to reduced time vulnerable to predators.	DDben	Degree days	GLORYS
			(H27) Food availability impacts growth and survival.	ZOOben	Zooplankton availability	Leising et al. (2024)
			(H28) Length of the upwelling season impacts nutrient and food availability which contributes to growth and survival.	LUSI	Length of Upwelling Season Index	Leising et al. (2024)

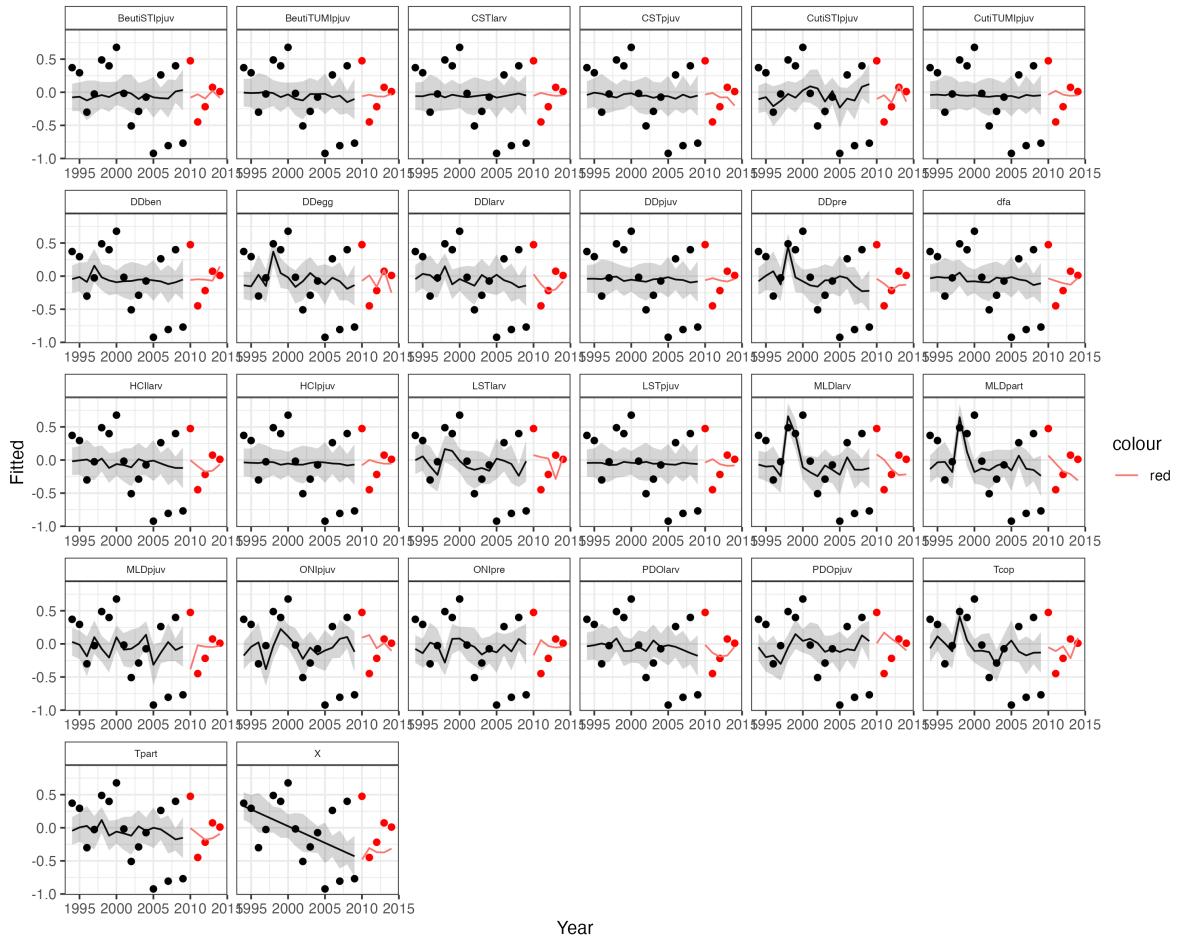


Figure 28: Univariate LM model fits with data from 1993 - 2009 and predicting the last 5 years of data one year at a time. Points denote obesrvd recruitment deviations and line denotes model predictions

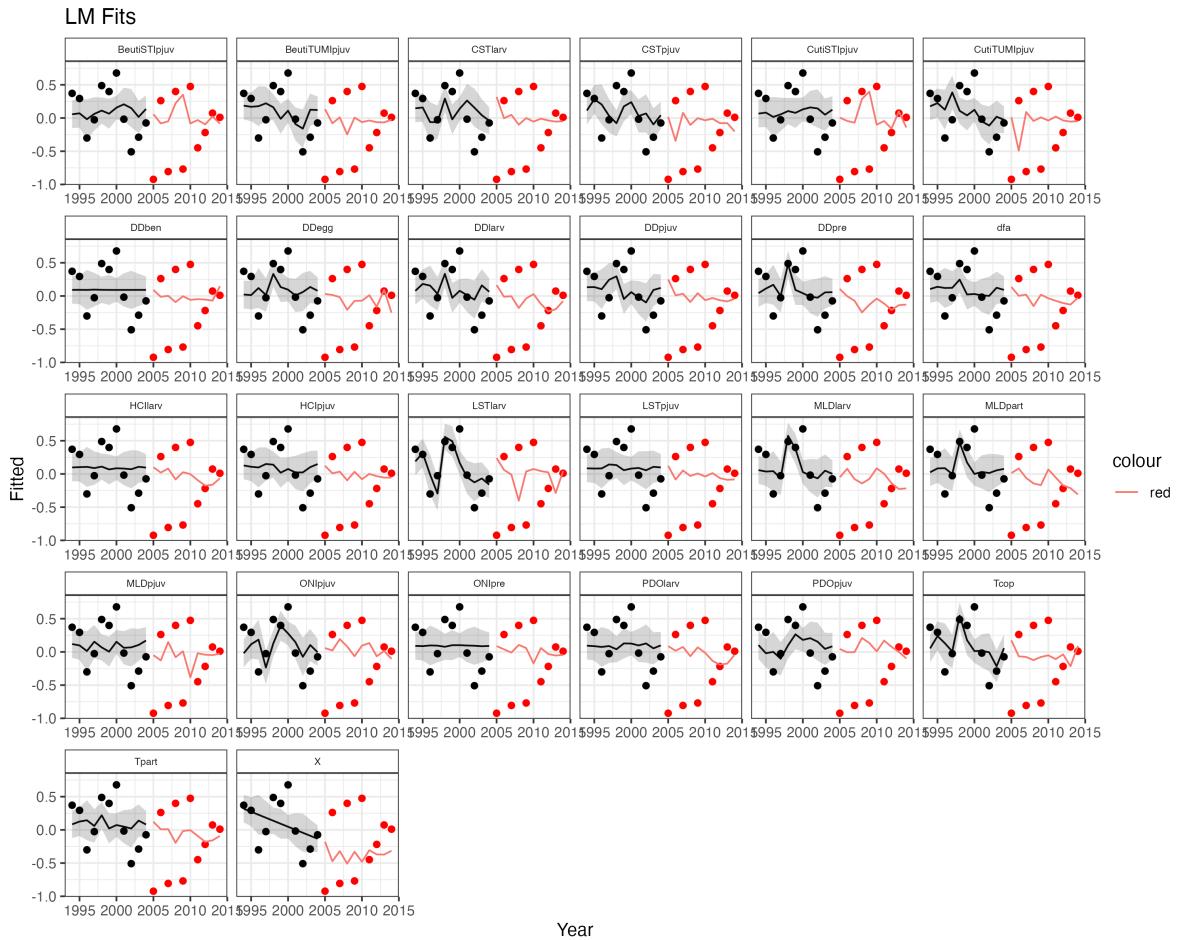


Figure 29: Univariate LM model fits with data from 1993 - 2004 and predicting the last 10 years of data one year at a time. Points denote obesrvd recruitment deviations and line denotes model predictions

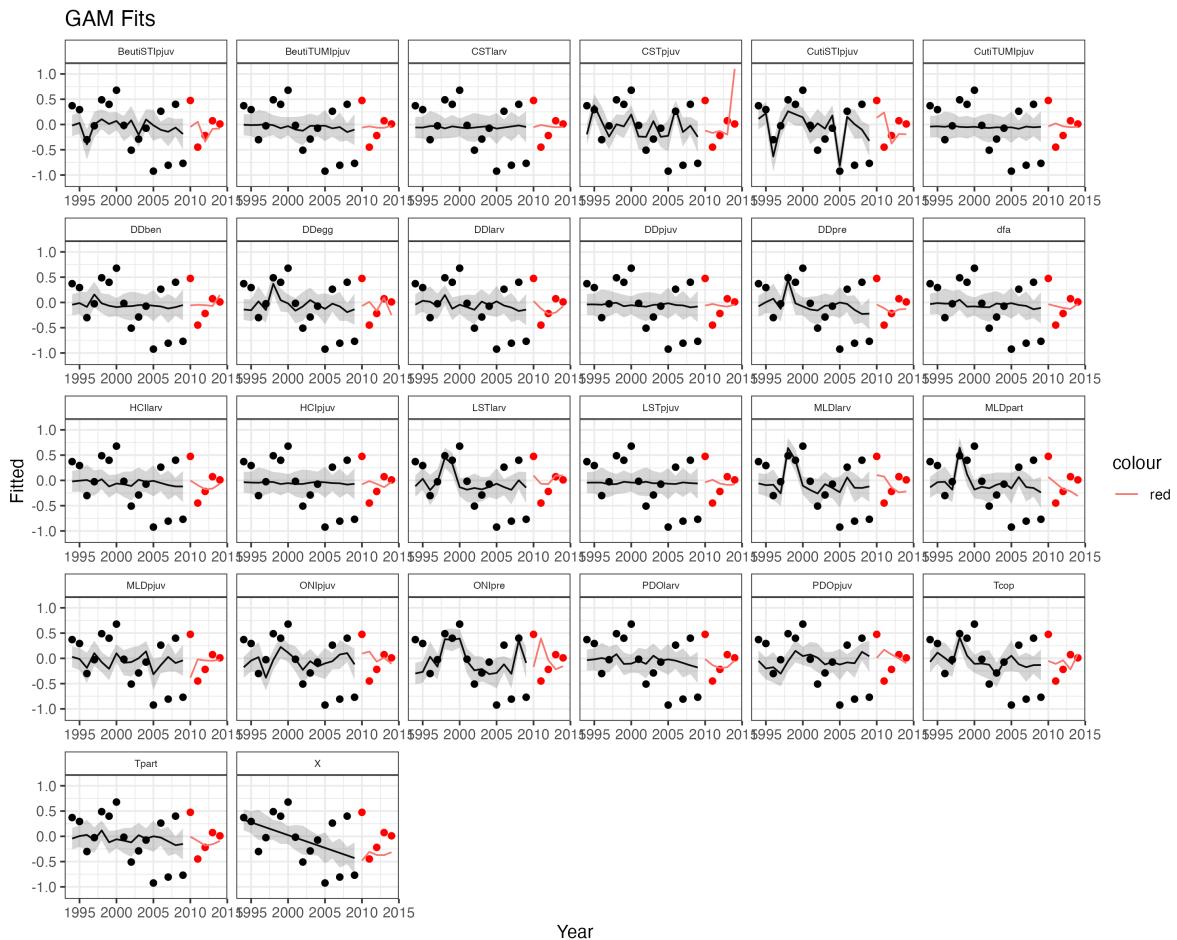


Figure 30: Univariate GAM model fits with data from 1993 - 2009 and predicting the last 5 years of data one year at a time. Points denote obesrvd recruitment deviations and line denotes model predictions

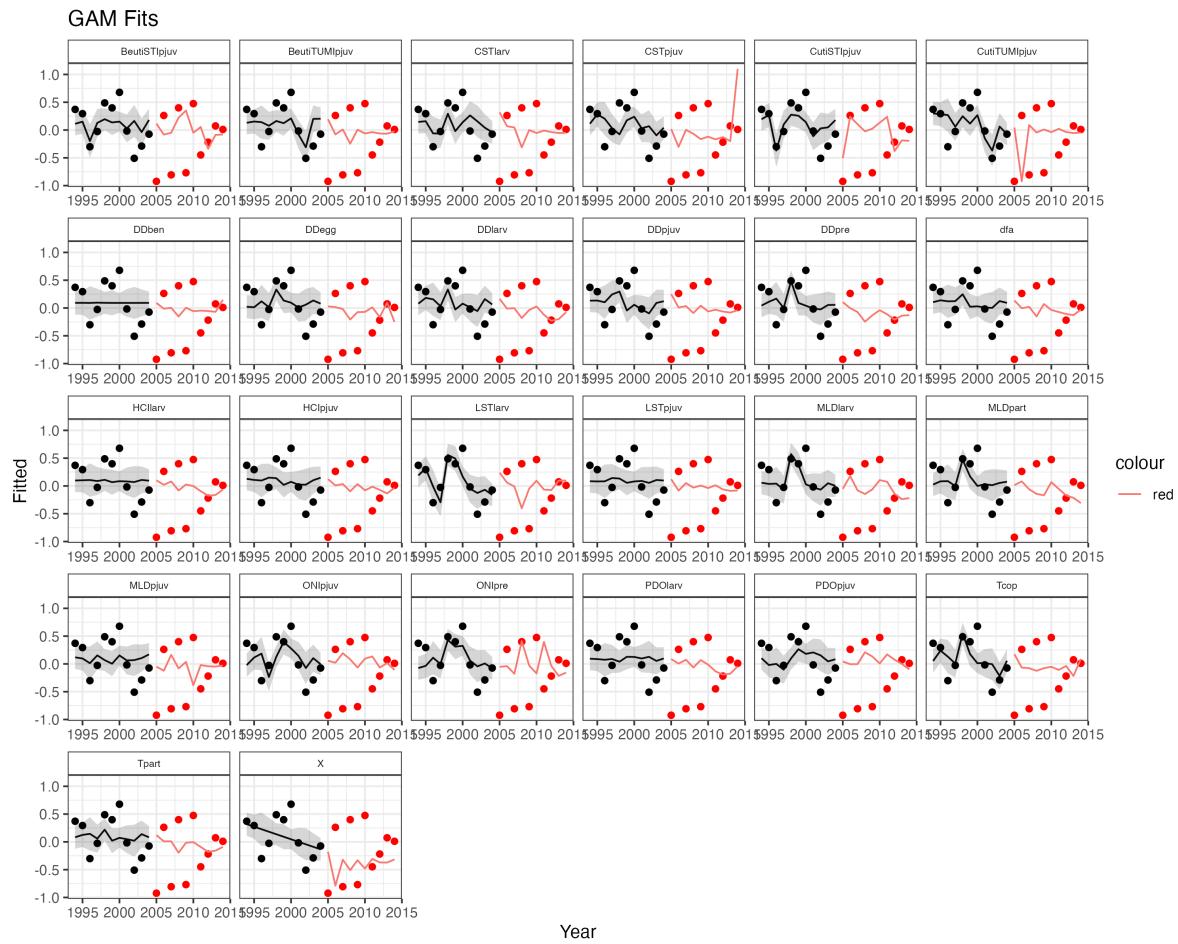


Figure 31: Univariate GAM model fits with data from 1993 - 2004 and predicting the last 10 years of data one year at a time. Points denote obesrvd recruitment deviations and line denotes model predictions