YellowtailNorthSummary

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A.1 Oceanographic indicators of northern Yellowtail

Darby et al. In Prep examined the relationship between recruitment deciations 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 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 Pacific hake assessment (citation). Upwelling conditions were not available from GLORYs and thus a ROMs upwelling time series was used.

The study area encompassed the region from Xlat to Ylat in teh 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 varibles explaining 65% of the deviation in recruitmnet deviations. Recruitment deviations were:

(1) Negatively associated with later spring transition of the upwelling season derived from the Coastal Upwelling Transport Index (CutiSTIpjuv)

(2) Recruitment is maximized when mixed layer depth at the larval stage (MLDlarv) is one standard deviation above average

(3) Recruitment is maximized when HCI during the larval stage (HCIlarv) is at average values

(4) Recruitment is maximized when long-shore transport during the larval stage (LSTlarv) 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 oceanogrphic 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.

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 1), many of which convary within each grouping (Figure 2)

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.

For linear model approaches, we find that the improvement in RMSE depends on selection criteria used (Figure 3). When applying LOO-CV, only five oceanographic conditions improved RMSE relative to a year predictor. T_{cop}, MLD_{part}, MLD_{larv}, DD_{pre}, and $CutiSTI_{pjuv}{}^2$ 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 $CutiSTI_{pjuv}{}^2$ were the top 5 predictors.Relative RMSE improvement was much higher using LFO-CV, where nearly all oceanogrpahic 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 3). 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_{cop},PDO_{larv}, HCI_{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

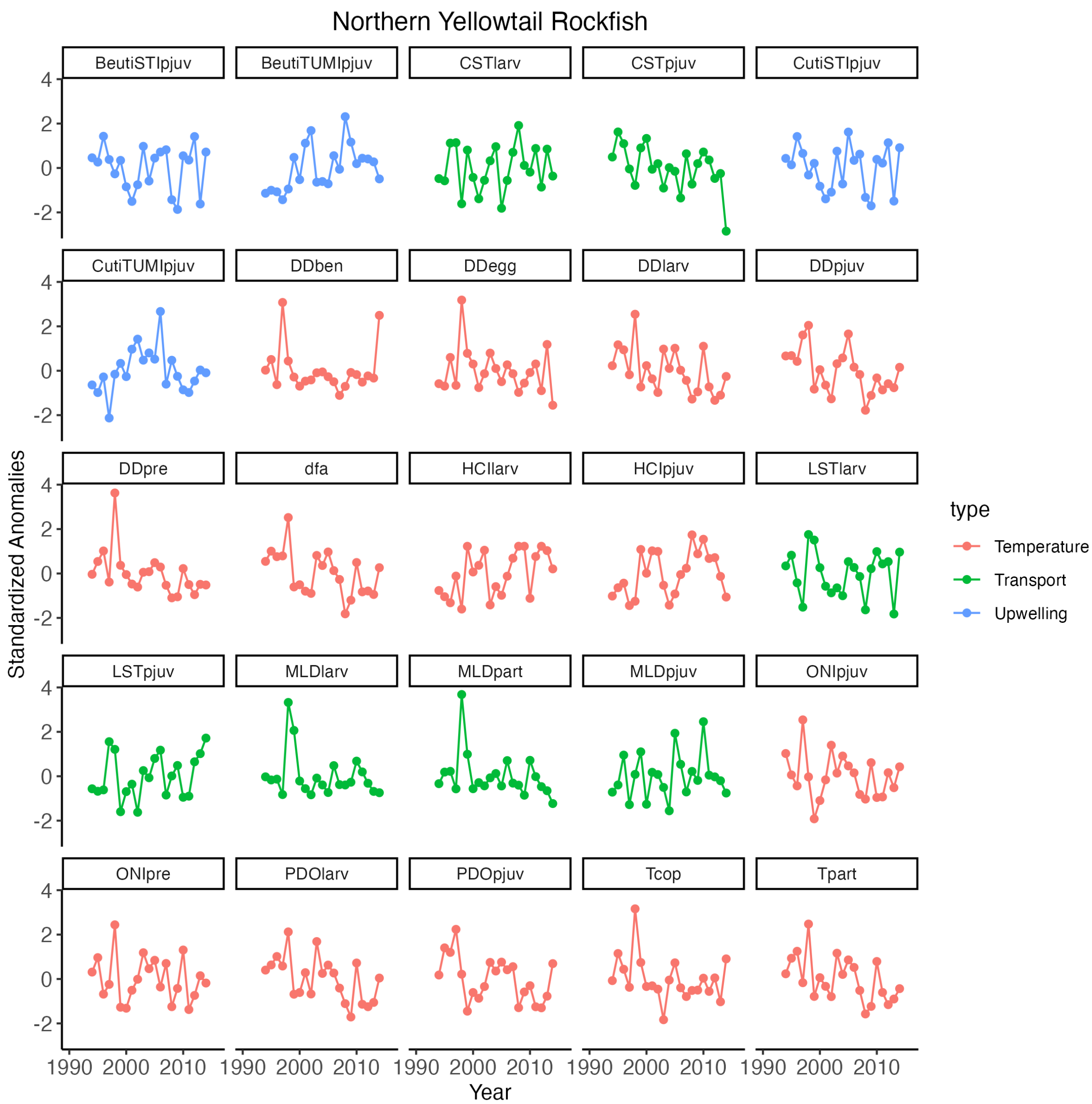

Figure 1: Time series of oceanographic conditions associated with northern Yellowtail rockfish recruitment

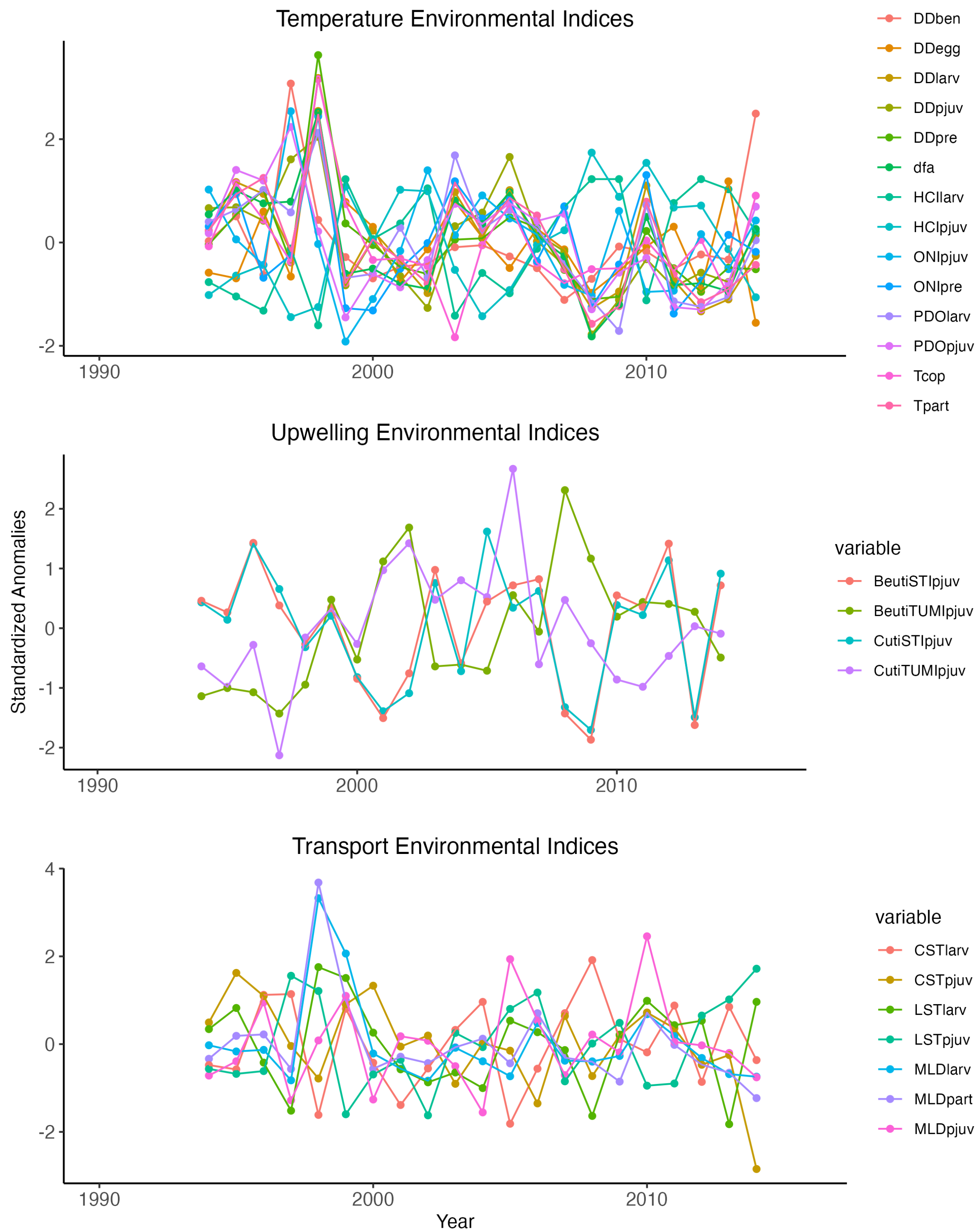

Figure 2: OceanographicTS2

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.

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.	DDpre	Degree days	GLORYS
			(H2) El Niño/La Niña cause shifts in temeprature and precipitation which lead to changes in recruitment success.	ONIpre	Ocean Niño Index	Leising et al. (2024)
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.	Tpart	Temperature	GLORYS
			(H6) Location of mixed layer depth may limit where in the water column mothers give birth.	MLDpart	Location of mixed layer depth	GLORYS

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
Larvae	Feb - Mar	0 - 90 m	(H7) Growth/predation hypothesis: Growth rate is faster in warmer water, leading to reduced time vulnerable to predators.	DDlarv	Degree days	GLORYS
			(H8) Cross-shelf transport to settlement habitat affects recruitment.	CSTlarv	Net cross-shelf transport	GLORYS
			(H9) Long-shore transport to settlement habitat affects recruitment.	LSTlarv	Net long-shore transport	GLORYS
			(H10) Location of mixed layer deph may limit where they are able to move in the water column, affecting transport and recruitment.	MLDlarv	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.	HCIlarv	Habitat Compression Index	Leising et al. (2024)
			(H12) El Niño/La Niña cause shifts in temeprature and precipitation which lead to changes in recruitment success.	ONIlarv	Ocean Niño Index	Leising et al. (2024)

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
			(H13) Changes in wind speed and direction impact upwelling/downwelling processes, ultimately impacing recruitment.	PDOlarv	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
			(H16) Long-shore transport to settlement habitat affects recruitment.	LSTpjuv	Net long-shore transport	GLORYS
			(H17) Location of mixed layer deph 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)

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Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
			(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 impacing 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)
			(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)

(continued)

Stage	Time.period	Depth	Hypothesis	Name	Covariates	Data.Source
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)

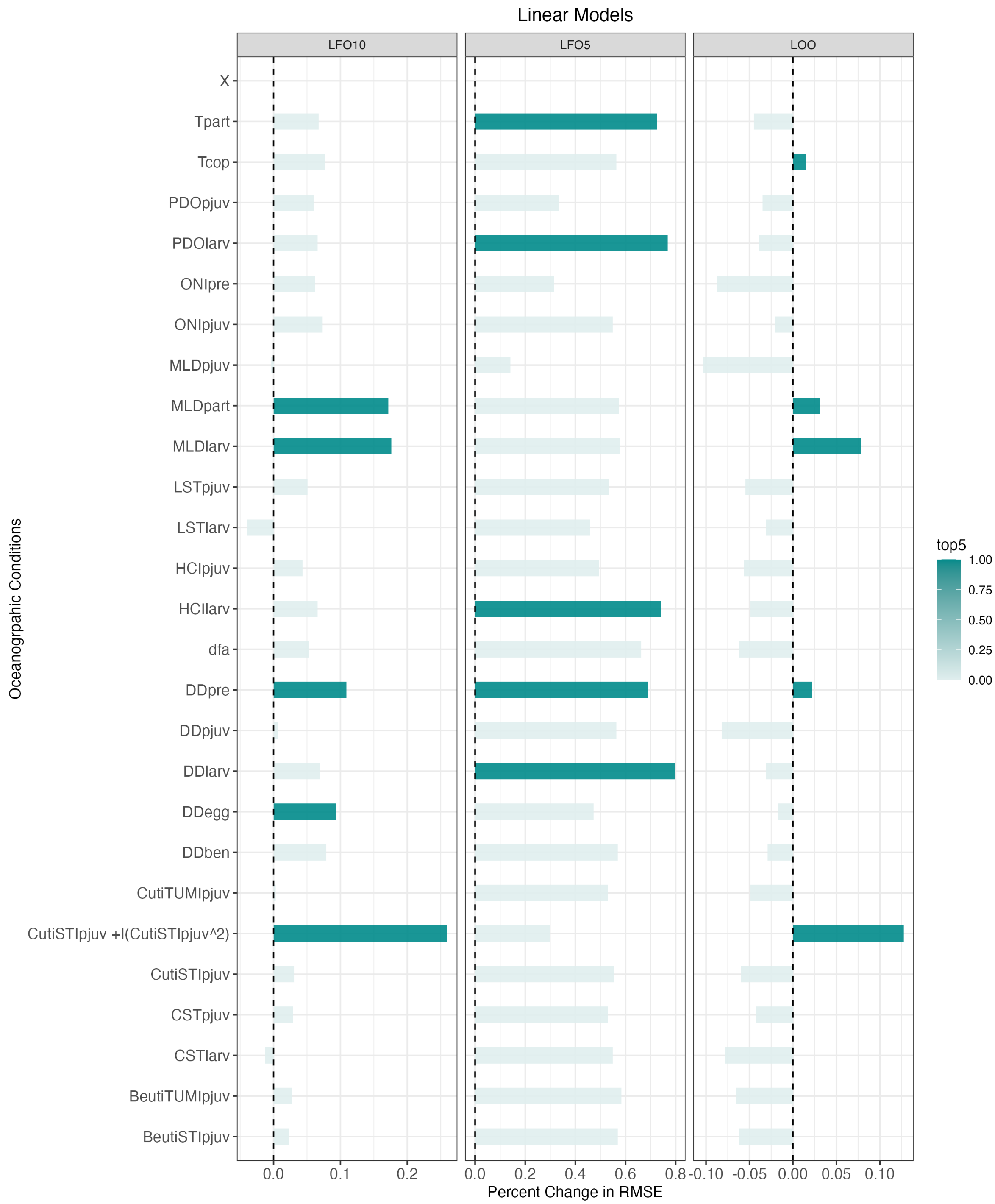

Figure 3: The top 5 ranked covariates for linear models using LOO-CV and LFO-CV predicting the last 5 and 10 years of data. RMSE impovement is relative to a using year only. Darker color indicates the top 5 ranked models

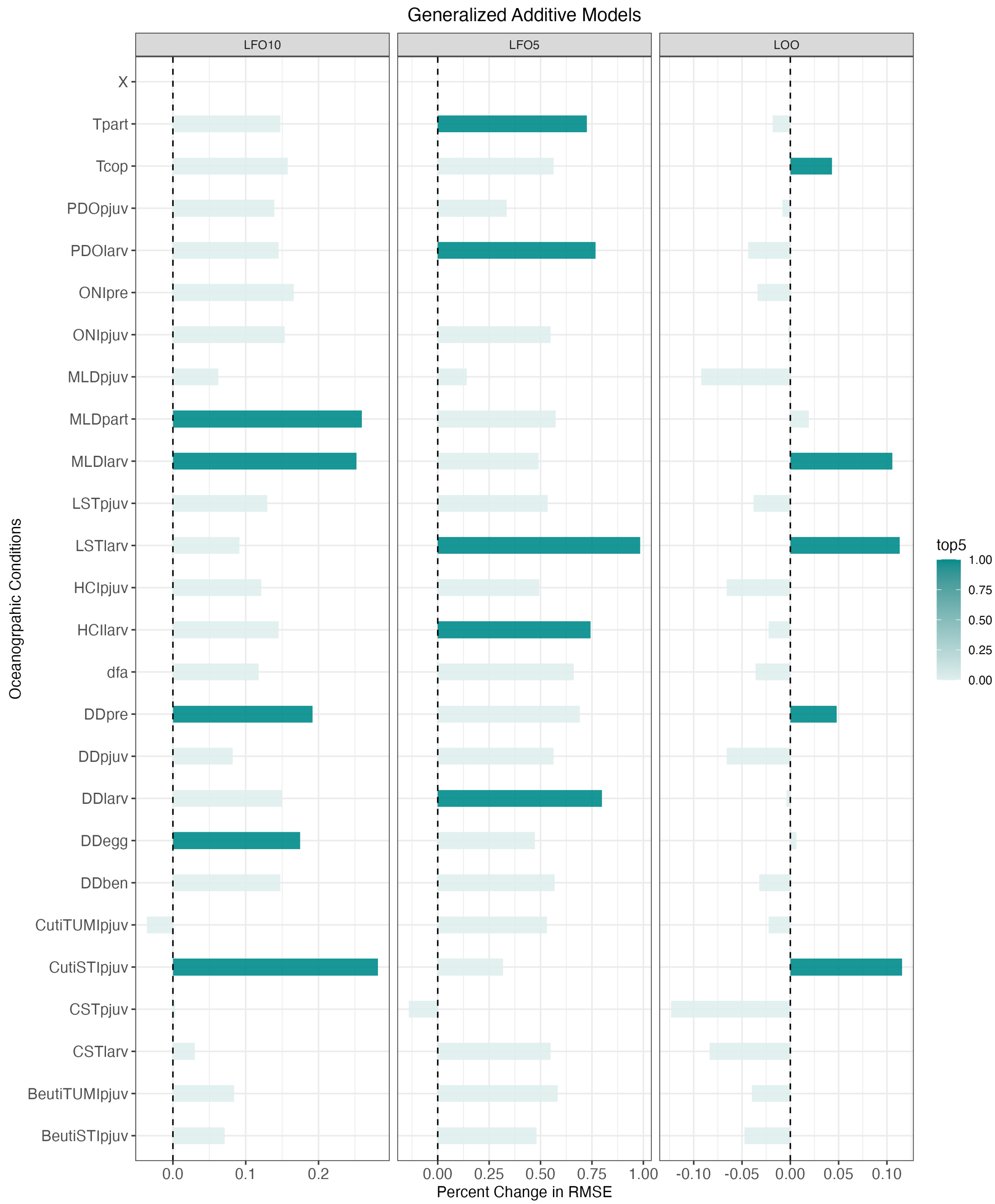

Figure 4: The top 5 ranked covariates for generalized additive models using LOO-CV and LFO-CV predicting the last 5 and 10 years of data. RMSE impovement is relative to a using year only. Darker color indicates the top 5 ranked models