Finding suitable weather indices for novel fisheries index insurance using machine learning

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Index insurance is a financial tool gaining traction for application in fisheries. It will cover fishers losses under extreme weather events that impact fishery productivity. This is the first assessment to determine the feasibility of such programs and whether suitable indices exist.

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1 Introduction

Predicting fishery output from weather variables is notoriously difficult. It is widely established that climate and weather affect fishing populations (Lehodey *et al.* 2006), but most stock assessment models use little to no year to year environmental data (Privitera-Johnson and Punt 2020). Variations in environmental conditions are now the leading cause of fishery closures and disaster relief payouts in the United States (Bellquist *et al.* 2021). Disaster declarations are becoming more frequent straining a slow, inequitable system (Holland and Leonard 2020; Jardine *et al.* 2020). Calls for new financial tools to alleviate fisher income shocks have grown (Mumford *et al.* 2009; Sethi 2010).

Index insurance has risen as a prime candidate tool to protect fishing communities during disasters (Watson *et al.* 2023). Index insurance is a financial product that pays out when an independently verified index, such as rainfall or temperature, falls below a predetermined threshold. The index is chosen to be highly correlated with the asset being insured. However, it is difficult to establish clear, concise weather impacts on fishery productivity. The biological dynamics of the system can lead to lower stock health persisting for years after a negative shock (**Hilborn2003?**). Individual fisheries can cover enormous areas in ocean basins. The expansive spatial coverage of fisheries makes it unclear where and how much specific weather variables impact biological abundance. In addition, if weather impacts have been observed, they are most likely highly non-linear adding further complexity. The greatest impediment to the development of fishery insurance policies is reconciling these challenges to find suitable indices that can predict fishery productivity (Watson *et al.* 2023).

Recent expansions in oceanic remote sensing has led to a wealth of new environmental indices that could be used to predict fishery productivity. Fishery data collection continues to improve with better reporting systems with longer and more detailed catch histories. This study aims to leverage these improved data sources to create suitable indices for fisheries index insurance using machine learning.

The difficulty in modelling fishery productivity with environmental indices leads to basis risk. Formally, basis risk is the probability that policyholders experience a harmful shock to their income, but the index does not trigger. Basis risk lowers demand for index insurance and remains a significant roadblock in setting up new programs (Binswanger-Mkhize 2012; Clarke 2016; Clement *et al.* 2018). Designing indices with stronger correlations to fishery losses is the most effective way to reduce basis risk (Jensen *et al.* 2019).

It is impossible to completely eliminate basis risk, and there exists a wide range in deployed agriculture products. Well designed policies can capture up to 90% of the income variation as shown in Kenyan pasture grazing indices (Jensen *et al.* 2019). Abysmal correlations are prevalent in the United States, where the Rainfall Index Insurance for Pasture, Rangeland, and Forage (RI-PRF) program has correlations as low as 0.071 in California leading to 46% additional basis risk (Keller and Saitone 2022). The program has a 26% probability of not paying out when damages are suffered in Nebraska and Kansas (Yu *et al.* 2019). Subsidies

covering up to 60% of ranchers paid premiums are need to stimulate demand in the RI-PRF program (Goodrich *et al.* 2019).

Contract design can mitigate basis risk through providing more options so that individuals can better select policies that protect them. Policyholders choose lower trigger levels when correlations between between index and asset are low (Lichtenberg and Iglesias 2022). Lower trigger levels correspond to protection against more catastrophic shocks. Increased contract flexibility reduces basis risk by only small amounts. Yu *et al.* (2019) found that more flexible contracts could account for only 5-9% of basis risk. Farms in Kansas closer to weather stations had better predictive impacts of rain on yield (Yu *et al.* 2019).

Machine learning has exploded as a new tool to define new and better indices in agriculture index insurance (Feng *et al.* 2019; Cesarini *et al.* 2021; Schmidt *et al.* 2022; Chen *et al.* 2024). Machine learning models excel in index insurance because indemnity contracts only need predictive relationships. Whereas, fishery stock assessments build complex models with biological foundations to accurately inform management of future fish stocks, index insurance can look retroactively at data to uncover relationships and test out of sample predictive quality. Machine learning may be necessary in fisheries index insurance to uncover any valuable relationships between weather and productivity.

The application of machine learning is growing in fisheries as researchers explore data questions beyond formal stock assessments. Ensemble models built through combinations of random forests, boosted trees, and dynamic linear models improved Bristol Bay sockeye salmon forecasts by 15% compared to a standard lagged regression model (Ovando *et al.* 2022). Environmental variables of importance to groundfish populations in Alaska were uncovered using single index varying coefficient models regularized with LASSO (Correia 2021). Random Forests models better predict fish catch in Indonesia than traditional linear models (Rahman *et al.* 2022). The expected non-linear interactions of weather and fishery productivity merit the use of machine learning in fisheries.

This study will provide the first comprehensive examination of the necessary features of weather indices for fisheries index insurance. We contribute to the growing ocean adaption and blue finance literature.

The rest of the paper is structured as follows. Section 2 describes the insurance model tested in this study. Section 3 describes the data used in this study. Section 4 describes the methods used to predict fishery productivity and evaluate the utility of index insurance. Section 5 presents the results of the study. Section 6 discusses the results and implications for the future of fisheries index insurance.

2 Insurance Model

Insurance contracts are specified by calculating payout functions ($I(\omega)$) based on independently measured weather variables. Neural networks have been used to provide non-linear payoff

schedules that better reduce basis risk (Chen *et al.* 2024). While it has been shown that linear payoff functions inherently lead to basis risk and therefore lower demand (Clarke 2016; Jensen *et al.* 2016), we maintain their use to preserve measures of interpretability that are clearer for a first analysis of fishery index insurance.

Payouts will be issued when prediction models predict negative deviations from long run average value. The three prediction models ($k \in \{$LR,LA,RF$\}$ are a linear regression (LR), a LASSO regression (LA), and a random forest (RF).

$$I(\omega) = \max(0, (\bar{\pi} - \hat{\pi}_t^k(\omega)) \cdot l) \tag{1}$$

Where k is the prediction model, l is the level of coverage, $\hat{\pi}_t^k(w)$ is the predicted fishing variable from ω weather variables, and $\bar{\pi}_x$ the long run average of the fishing variable. The premium is calculated as the expected value of the payout function times the premium loading factor (m).

$$\rho(\omega) = \mathbb{E}[I(\omega)]m \tag{2}$$

Utility measures offer the most insightful evaluation of index insurance policies (Kenduiywo *et al.* 2021). It captures value added for policyholders, not just measures of payout frequency as other measures of basis risk. Constant absolute risk aversion allows more consistent comparison for different levels of wealth. Expected utility for a given fishery is the average utility over all years in the sample for any variable of interest π_t. Fishers are allowed to choose insurance coverage levels l to ensure feasible contracts.

$$
\begin{aligned}
\mathbb{E}[U_b] &= \frac{1}{n} \sum_t^T \frac{1 - e^{-a\pi_t}}{a} & \text{No Insurance} \\
\mathbb{E}[U_i] &= \max_l \frac{1}{n} \sum_t^T \frac{1 - e^{(-a(\pi_t + I(\omega, l) - \rho(w))}}{a} & \text{Insurance} \\
U_r &= \frac{\mathbb{E}[U_i] - \mathbb{E}[U_b]}{\mathbb{E}[U_b]} \cdot 100 & \text{Percent Change in Utility}
\end{aligned}
\tag{3}
$$

We will compare the percent change in fisher utility with insurance (U_i) versus without insurance (U_b) for each prediction method. The variable of interest π_t, will be fishing revenue, landings, and catch per fisher to test what measures of fishery productivity are most suitable for index insurance.

No data on fishery insurance suppliers exists to create a market equilibrium. We iteratively vary the premium loading $m \in [1, 2]$ to create a range of coverage values fishers will be willing to pay for a given m. Then, the amount of coverage purchased times the premium loading factor approximately equals the expected revenue an insurance company would receive. Insurance

companies could then examine their own administrative and legal costs to determine whether the feasible contract is profitable.

3 Data

This study attempts to cover breadth, not depth in possible indices. Each fishery has unique ecological characteristics that interact with environmental variables in different and non-linear ways. By studying a wide collection of fisheries and environmental variables we can uncover the potential feasibility of index insurance for fisheries holistically, and then further refine measures with ecologically sound models in the future.

3.1 Fishery Data

Landings revenue, and participation data comes from the West Coast Fish data package (Free *et al.* 2022). It is a reconstruction of California Fish and Wildlife Department catch data combined with PacFin receipts for Washington and Oregon. The last three years of data are updated from the CDFW Marine Fisheries Data Explorer (MFDE). Names are matched to each species within the West Coast Fish data package.

We select California fisheries with a minimum of 30 years of consecutive, non-confidential catch records at both the state and port-complex level. Unclassified catch records are dropped i.e. "Other Sharks" and similar categories. Fisheries with an average revenue greater than $100,000 at the state and $75,000 at port-complex level are analyzed. Twenty four fisheries at the state level and 49 fisheries at the port complex level meet these criteria. These fisheries contain the most economically important fisheries in California and their mean values are shown in Table 1 and at the port complex in Table 2.

Fisheries have complex spatial dynamics. Agriculture has clear, quantifiable impacts of weather in grids that are well suited for index insurance. Drought on a single farm directly leads to crop loss for that farm. Whether there is sufficient spatial coverage to identify impacts down to an individual farm remains a challenge in agriculture (Dalhaus and Finger 2016; Leppert *et al.* 2021; Stigler and Lobell 2024). Fish and fishers can move thousand of miles in a given year, thus more consideration must be given to the location of weather impacts in fisheries. We spatially refine catch histories using the California CDFW fishing blocks records from the MFDE Data Explorer. Summarized catch histories of all landed fish within each block provide an average representation of effort for a given fishery. Spatial catch history is measured at both the state and port-complex level. The spatial location refines the location of environmental variables. Local weather is more likely to affect fishery productivity and catch than observations thousands of miles away.

3.2 Environmental Data

Fisheries are highly sensitive to marine heatwaves and water temperature. Sea surface temperature is a natural variable to first consider in fisheries index insurance. Sea surface temperature data comes from the NOAA DHW data set that provides 5-km resolution of monthly temperature from 1985 to 2023. The 5-km grids are averaged within the nearest California fishing block to provide an annual time series of temperature for each fishery. Temperature is lagged from 1 to 3 years prior to account for residual impacts that carry over due to fishery biological dynamics.

Upwelling provides vital nutrients to stimulate primary productivity. The coast of California is a highly productive ecosystem due to its patterns of upwelling (Chelton *et al.* 1982; Huyer 1983). We capture upwelling through monthly observations of Coastal Upwelling Transport Index (CUTI) and Biological Effective Upwelling Transport Idnex (BEUTI). Both indices create measures of vertical movement in the mixed layer at 1 degree latitude intervals extending 75 km along the entire US West Coast (Jacox *et al.* 2018). The closest layer to the surface was used in this analysis as the correlation between surface index values and deeper index values are high. CUTI examines the physical measures of wind, ekman transport, and cross-shore geostrophic transport to indicate the strength of upwelling in a given month. BEUTI adds nitrate concentration in its calculation to capture more biological effects of upwelling. Fishing blocks are matched to the nearest 1 degree latitude interval to provide a monthly time series of upwelling for each fishery. Seasonal strengths of upwelling are captured by averaging CUTI and BEUTI within each quarter of the year. Spring upwelling in early March and April are espeically important to a wide array of fish species. Yearly average and amplitude values (the difference between minimum observed upwelling and maximum) are also calculated. These indices are the most temporally limited datasets in this analysis, only extending from 1988 to 2023.

The Habitat Compression Index measures the area extent of water below average temperatures thresholds along the US West Coast (Schroeder *et al.* 2022). Habitat compression is a measure of the spatial extent of cold water habitats that are important for fish species. The index is broken down into four distinct oceangraphic regions ranging from 3.5 degrees to 5.5 degrees lattitude in size with coverage out to 150 km offshore. We use the cumulative habitat compression index that sums the index value in each month to provide a yearly time series of habitat compression for each fishery. The cumulative index showed stronger correlations with biological productivity measures than monthly measures (Schroeder *et al.* 2022)

The final environmental variables are the Pacific Decadal Oscillation (PDO) and the El Nino Southern Oscillation (ENSO). Both indices are well known to affect marine ecosystems and fisheries. Both indices are averaged over a given year. PDO data is taken from the PDO ERSST V5, and ENSO data is taken from the multivariate ENSO Index Version 2 (MEI.v2).

Summary statistics for the environmental data are presented in **?@tbl-env-sum**. In total, 73 fisheries with 35 years of catch data are matched to 20 spatial matched environmental variables

with annual coverage from 1988 to 2023.

4 Methods

We use three models to predict yearly fishing revenue, landings, and catch per fisher at state and port-complex levels. Linear models are used as the base model given its ubiquitous use in index insurance policies. We compare utility improvements with the adoption of more robust LASSO regression and random forest models.

In all class of models, the final utility maximization choice of coverage leverage is found through a box constrained quasi-Newton Method using the optim function in R. Choices are constrained between zero and the fishing variable's average value. Premium schedules are found by the model output below the trigger values in Equation 1 and then averaged over the time period.

4.1 Linear Models

Perfect regression coefficients mimic the optimal choice of scale in index insurance contracts (**Mahul1999?**). Combined with the ease of implementation, linear models on single weather indices are the most common design choice for index insurance policies. They offer a basic starting place to consider the viability of fishery index insurance.

Yearly aggregated fishing variables are regressed on each spatially matched to catch environmental variable. We perform a 10 fold cross validation method to determine the best individual weather variable based on root mean square error (RMSE). To preserve the time series element of the data, we used a rolling split to partition the training and testing data. For example, the first fold contains the first 70% of data as training (1988-2011), and the last 30% as testing (2013-2023). The final date of the training set is extended in each fold until the year 2020 to create 10 folds. Models with the lowest average RMSE are selected and trained on the full set before being passed to the utility optimization procedure in Equation 3.

4.2 LASSO Regression

Least Absolute Shrinkage and Selection Operator (LASSO) regression is a popular regularization technique to assist model selection. It attempts to minimize the residual sum of squared errors through Ordinary Least Squares (OLS), but adds a penalty constraint on the absolute sum of selected coefficient values (Equation 4).

$$\widehat{\beta}^{lasso} = \arg\min_{\beta} \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \omega_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{4}$$

Where, y_i is our fishing variable, β the regression coefficients, n, the number of observations, p the number of predictors, and ω the total collection of weather variables. The λ is the penalty term that controls the amount of shrinkage. The LASSO regression model is trained on the same 10 fold cross validation method as the linear models. The optimal λ is selected through a grid search method that selects the RMSE one standard error away from the minimum. This choice is to ensure the most parsimonious model that still captures the most important weather variables. LASSO is particularly well suited for this research design as the absolute value of the penalty term shrinks coefficients to zero. Overfitting is a concern with so few observations in the initial training set; the shrinkage towards zero will help minimize this bias.

4.3 Random Forests

While LASSO offers us the ability to simultaneously explore a wide collection of weather variables including lagged effects, it remains linear in its predictions. Random Forests are tree-based ensemble models that capture non-linear interactions through recursive partitioning. The are less sensitive to over fitting through the aggregation of many trees.

We tune three hyperparameters to create the best performing random forest for each fishery. The number of trees in the forest, the number of variables to consider at each split, and the minimum number of observations in a leaf node. We use a grid search method to find the best hyperparameters based on RMSE. The final model is trained on the full dataset and passed to the utility optimization procedure in Equation 3.

5 Results

6 Discussion

7 Appendix

Table 1: Summary statistics of catch from 1988-2023 for California fisheries.

| | Landings (mt) | | Revenue (USD) | | MT per Fisher | | Numb |
Species	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Devation	Average
Albacore	2055.4	2646.5	$3,574,984	4051538.3	5.3	3.1	305.5
Bluefin tuna	760.5	1131.1	$1,118,896	1137192.5	9.3	12.1	76.3
California spiny lobster	314.6	69.6	$7,752,729	5402314.5	1.7	0.6	202.0
Chinook salmon	1576.1	1291.7	$10,383,616	7643140.9	1.5	1.1	1146.6
Chub mackerel	11304.3	10208.0	$1,944,342	1709450.2	80.2	59.5	133.9
Dungeness crab	5712.8	3334.7	$29,115,960	23070113.4	11.6	7.9	534.5
Market squid	51363.6	34634.6	$27,517,541	24057582.4	462.1	289.5	109.4
Nom. Cabezon	35.3	38.7	$306,669	321874.4	0.2	0.1	199.0
Nom. Calif halibut	374.6	140.9	$2,605,362	873979.0	0.9	0.3	427.1

Species							
Nom. California sheephead	46.7	38.8	$342,986	231782.3	0.4	0.2	134.1
Nom. Lingcod	359.0	421.0	$388,778	276453.1	0.4	0.3	675.4
Nom. Shortspine thornyhead	56.4	70.0	$432,850	465662.0	0.5	0.6	116.2
Northern anchovy	7696.1	10157.9	$860,871	643585.4	230.8	246.9	32.7
Opah	102.4	100.0	$198,182	257248.5	2.5	3.6	71.0
Pacific bonito	1090.7	1694.6	$544,835	886379.0	8.7	10.3	108.2
Pacific sardine	20665.4	22757.5	$2,574,205	2614838.8	309.1	325.9	53.3
Red sea urchin	7947.2	6067.5	$11,443,321	7684762.0	32.7	12.7	231.1
Ridgeback prawn	172.8	146.5	$634,305	473336.8	7.7	5.7	26.1
Rock crab	620.2	146.3	$1,750,541	597289.3	3.6	1.2	180.7
Sablefish	2753.2	1823.2	$5,759,976	2768043.7	10.4	6.9	269.6
Spotted prawn	153.1	76.1	$3,206,726	1989792.4	3.7	2.3	52.6
Swordfish	808.3	554.7	$5,671,198	3401866.3	6.7	3.2	129.3
White seabass	109.2	76.4	$635,876	429179.6	0.8	0.7	150.3
Yellowfin tuna	8853.7	17403.5	$10,230,193	20959459.4	67.4	89.0	74.0

Table 2: Summary statistics of catch from 1988-2023 for Californi
species and port complex

Species	Port	Landings (mt)		Revenue (USD)	
		Average	Standard Deviation	Average	Standard Deviat
Albacore	Eureka	355.0	377.4	$672,866	63489
	San Francisco	175.8	368.5	$322,734	63977
Bluefin tuna	San Diego	25.2	38.5	$163,167	33464
Nom. Calif halibut	Los Angeles	47.2	36.2	$303,840	17262
	San Diego	17.9	12.3	$117,380	5109
	San Francisco	140.4	64.0	$1,053,595	72143
	Santa Barbara	97.9	44.4	$705,370	18739
Chinook salmon	Bodega Bay	329.6	309.3	$2,258,504	198996
	Eureka	103.6	178.4	$649,797	100083
	Fort Bragg	343.9	404.8	$2,320,248	236783
	Monterey	313.7	272.7	$1,896,626	116152
	Morro Bay	72.9	81.4	$493,105	51598
	San Francisco	493.7	348.0	$3,339,479	207526
Chub mackerel	Los Angeles	10320.4	9344.1	$1,782,814	156121
	Bodega Bay	572.9	554.1	$3,390,721	351059
	Eureka	3571.6	2232.7	$16,072,727	1267263
	Fort Bragg	247.3	191.4	$1,376,466	143730

Dungeness crab

	Monterey	91.7	104.4	$692,846	86878
	San Francisco	1174.3	1276.2	$7,090,167	803565
California spiny lobster	Los Angeles	98.3	21.3	$2,326,853	147185
	San Diego	99.0	22.5	$2,179,454	124446
	Santa Barbara	116.8	49.4	$3,239,108	289395
Market squid	Los Angeles	16986.5	14774.8	$8,750,561	892798
	Santa Barbara	24534.0	20112.5	$12,790,364	1330326
Opah	San Diego	58.6	66.2	$121,629	18225
Rock crab	Los Angeles	101.5	105.4	$259,159	19651
	Morro Bay	75.9	65.7	$183,343	12472
	San Diego	67.1	35.0	$163,988	7931
	Santa Barbara	344.2	173.1	$1,036,433	64137
Ridgeback prawn		155.5	139.5	$562,758	45359
Red sea urchin	Los Angeles	1229.8	1020.2	$1,890,768	136234
	Santa Barbara	3971.6	2451.7	$6,081,764	398720
Sablefish	Bodega Bay	90.7	90.1	$186,193	16654
	Eureka	886.0	607.5	$1,634,560	69191
	Fort Bragg	574.5	368.0	$1,221,487	63351
	Los Angeles	227.5	552.3	$321,915	46103
	Monterey	316.0	204.2	$642,984	41584
	Morro Bay	229.8	185.6	$679,713	93982
	San Diego	25.9	22.7	$137,336	14431
	San Francisco	336.2	320.6	$559,985	26897
	Santa Barbara	63.3	74.2	$352,529	47642
Nom. California sheephead	San Diego	13.9	11.3	$119,436	8415
	Santa Barbara	20.9	22.7	$134,335	12585
Spotted prawn		53.4	29.2	$1,116,708	87380
Swordfish	Los Angeles	315.9	360.1	$2,072,740	197240
	San Diego	178.4	131.0	$1,416,146	90558
	Santa Barbara	66.1	91.5	$466,637	58552
	Los Angeles	31.5	30.9	$146,996	11198

White seabass

San Diego	13.1	26.4	$73,176	8748
Santa Barbara	54.3	43.1	$331,544	26952

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