Supplemental Information: Full model tests and diagnostics

Tests for prior season catch as covariate

Table S1. Model selection tests of time-dependency the log catch during spawning months using F-tests of nested linear models. S_t is the catch during the spawning period (Jul-Sep). N_t is the catch during the non-spawning period (Oct-Jun). S_{t-1} and N_{t-1} are the catch during the prior season during and after the spawning period respectively. S_{t-2} and N_{t-2} are the same for two seasons prior. Test A uses catch during the spawning period as the explanatory variable. Test B uses catch during the non-spawning period as the explanatory variable. The numbers in front of the model equation indicate the level of nestedness. For Test C, there are two nested model sets, each with a different model 3. The Naive model is a model that uses the previous data point in the time series as the prediction; thus the Naive model has no estimated parameters.

Model	Residual df	MASE	Adj. R2	F	p value	AIC	LOOCV RMSE
Naive Model 1983-2015 data							
$ln(S_t) = ln(S_{t-1}) + \epsilon_t$	33	1				126.63	1.596
Time dependency test A 1983-2015 data							
1. $ln(S_t) = \alpha + ln(S_{t-1}) + \epsilon_t$	32	1	-29.1			128.9	1.646
2. $ln(S_t) = \alpha + \beta ln(S_{t-1}) + \epsilon_t$	31	0.83	9.8	15.28	0	118.46	1.43
3. $ln(S_t) = \alpha + \beta_1 ln(S_{t-1}) + \beta_2 ln(S_{t-2}) + \epsilon_t$	30	0.828	12.7	2.05	0.163	118.88	1.418
Time dependency test B 1983-2015 data							
1. $ln(S_t) = \alpha + ln(N_{t-1}) + \epsilon_t$	32	0.882	11			116.64	1.367
2. $ln(S_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	31	0.827	20	4.48	0.043	114.48	1.319
3. $ln(S_t) = \alpha + \beta_1 ln(N_{t-1}) + \beta_2 ln(N_{t-2}) + \epsilon_t$	30	0.832	17.4	0.04	0.846	117.04	1.357
Time dependency test C 1983-2015 data							
1. $ln(S_t) = \alpha + ln(N_{t-1}) + \epsilon_t$	32	0.882	11			116.64	1.367
2. $ln(S_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	31	0.827	20	4.49	0.043	114.48	1.319
3a. $ln(S_t) = \alpha + \beta_1 ln(N_{t-1}) + \beta_2 ln(S_{t-1}) + \epsilon_t$	30	0.835	17.6	0.09	0.768	116.98	1.383
3b. $ln(S_t) = \alpha + \beta_1 ln(N_{t-1}) + \beta_2 ln(S_{t-2}) + \epsilon_t$	30	0.812	18.6	0.47	0.496	116.56	1.34

Table S2. Model selection tests of time-dependency the catch during spawning months using non-linear or time-varying linear responses instead of time-constant linear responses as in Table S1. See Table S1 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC	LOOCV RMSE
Time dependency test A 1983-2015 data							
1. $ln(S_t) = \alpha + \beta ln(S_{t-1}) + \epsilon_t$	31	0.83	9.8			118.46	1.43
2. $ln(S_t) = \alpha + s(ln(S_{t-1})) + \epsilon_t$	29	0.81	19.9	2.73	0.085	116.75	1.363
3. $ln(S_t) = \alpha + s_1(ln(S_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	26.2	0.791	20.2	0.86	0.466	120.94	1.379
Time dependency test B 1983-2015 data							
1. $ln(S_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	31	0.827	20			114.48	1.319
2. $ln(S_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	29.6	0.798	21.7	1.12	0.321	115.22	1.313
3. $ln(S_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(N_{t-2})) + \epsilon_t$	27.3	0.793	18.9	0.36	0.732	119.59	1.352
Time dependency test C 1983-2015 data							
1. $ln(S_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	29.6	0.798	21.7			115.22	1.313
2. $ln(S_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-1})) + \epsilon_t$	26.9	0.722	26.7	1.59	0.218	117.02	1.285
3. $ln(S_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	26.8	0.763	23.4	1.06	0.381	118.61	1.312
Time varying test D 1983-2015 data							
1. $ln(S_t) = \alpha_t + \epsilon_t$	29	0.648				115.3	1.373
2. $ln(S_t) = \alpha_t + \beta_t t + \epsilon_t$	27	0.838				116.55	1.354
3a. $ln(S_t) = \alpha + \beta_t ln(S_{t-1}) + \epsilon_t$	28	0.713				117.14	1.49
3b. $ln(S_t) = \alpha + \beta_t ln(N_{t-1}) + \epsilon_t$	28	0.783				113.07	1.337

Table S3. Table S2 with 1956-1982 data instead of 1983 to 2015 data. See Table S1 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC	LOOCV RMSE
Time dependency test A 1956-1982 data							
1. $ln(S_t) = \alpha + \beta ln(S_{t-1}) + \epsilon_t$	23	0.611	1			62.58	0.809
2. $ln(S_t) = \alpha + s(ln(S_{t-1})) + \epsilon_t$	21.1	0.588	2.9	1	0.382	64.4	0.831
3. $ln(S_t) = \alpha + s_1(ln(S_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	18.9	0.545	8.3	1.42	0.267	67.06	1.023
Time dependency test B 1956-1982 data							
1. $ln(S_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	23	0.609	-3.7			63.76	0.814
2. $ln(S_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	20.6	0.558	10.1	2.44	0.109	63.27	0.77
3. $ln(S_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(N_{t-2})) + \epsilon_t$	17.4	0.466	18	1.44	0.264	67.62	0.783
Time dependency test C 1956-1982 data							
1. $ln(S_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	21.5	0.56	5.7			65.74	0.79
2. $ln(S_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-1})) + \epsilon_t$	19.7	0.524	9.2	1.31	0.289	68.21	0.814
3. $ln(S_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	18.6	0.521	15.5	1.49	0.252	65.73	0.972

Table S4. Model selection tests of time-dependency the N_t model using F-tests of nested models fit to 1983 to 2014 log landings data. The years are determined by the covariate data availability and end in 2014 since the landings data go through 2015 and N_{2014} includes quarters in 2014 and 2015. N_t is the catch during the non-spawning period (Qtrs 4 and 1: Oct-Mar) of season t (Jul-Jun). S_{t-1} and N_{t-1} are the catch during the prior sardine season during and after the spawning period respectively. S_{t-2} and N_{t-2} are the same for two seasons prior. Test A uses catch during the spawning period as the explanatory variable. Test B uses catch during the non-spawning period as the explanatory variable. Test C uses both. The numbers next to the model equations indicate the level of nestedness. The Naive model is a model that uses the previous data point in the time series as the prediction; thus the Naive model has no estimated parameters.

Model	Residual df	MASE	Adj. R2	F	p value	AIC	LOOCV
Naive Model 1983-2014 data							
$ln(N_t) = ln(N_{t-1}) + \epsilon_t$	32	1				92.73	0.999
Time dependency test A 1983-2014 data							
1. $ln(N_t) = \alpha + ln(S_{t-1}) + \epsilon$	31	1.379	-19.4			109.82	1.305
2. $ln(N_t) = \alpha + \beta ln(S_{t-1}) + \epsilon_t$	30	1.035	26.3	20.34	0	95.34	1.023
3. $ln(N_t) = \alpha + \beta_1 ln(S_{t-1}) + \beta_2 ln(S_{t-2}) + \epsilon_t$	29	1.02	26.8	1.21	0.281	96.03	1.048
Time dependency test B 1983-2014 data							
1. $ln(N_t) = \alpha + ln(N_{t-1}) + \epsilon_t$	31	1	25.5			94.73	1.031
2. $ln(N_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	30	0.987	37.5	6.74	0.015	90.05	1.048
3. $ln(N_t) = \alpha + \beta_1 ln(N_{t-1}) + \beta_2 ln(N_{t-2}) + \epsilon_t$	29	0.981	35.4	0.03	0.861	92.02	1.132
Time dependency test C 1983-2014 data							
1. $ln(N_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	30	0.987	37.5			90.05	1.048
2a. $ln(N_t) = \alpha + \beta_1 ln(N_{t-1}) + \beta_2 ln(S_{t-1}) + \epsilon_t$	29	0.973	35.6	0.11	0.746	91.93	1.078
2b. $ln(N_t) = \alpha + \beta_1 ln(N_{t-1}) + \beta_2 ln(S_{t-2}) + \epsilon_t$	29	0.987	35.4	0.01	0.923	92.04	1.191

Table S5. Model selection tests of time-dependency the N_t model using non-linear or time-varying linear responses instead of time-constant linear responses as in Table S4 See Table S4 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC	LOOCV
Time dependency test A 1983-2014 data							
1. $ln(N_t) = \alpha + \beta ln(S_{t-1}) + \epsilon_t$	30	1.035	26.3			95.34	1.023
2. $ln(N_t) = \alpha + s(ln(S_{t-1})) + \epsilon_t$	28.1	1.01	30	1.72	0.2	94.94	1.007
3. $ln(N_t) = \alpha + s_1(ln(S_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	25.1	0.955	36.6	1.84	0.167	93.76	1.004
Time dependency test B 1983-2014 data							
1. $ln(N_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	30	0.987	37.5			90.05	1.048
2. $ln(N_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	28.6	0.879	45.9	4.06	0.042	86.3	0.955
3. $ln(N_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(N_{t-2})) + \epsilon_t$	26.4	0.813	46.1	0.87	0.443	87.71	1.013
Time dependency test C 1983-2014 data							
1. $ln(N_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	28.6	0.879	45.9			86.3	0.955
2. $ln(N_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-1})) + \epsilon_t$	26	0.859	44.6	0.58	0.615	88.93	1.057
3. $ln(N_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	25.6	0.748	57.3	3.43	0.032	80.76	1.055
Time varying test D 1983-2014 data							
1. $ln(N_t) = \alpha_t + \epsilon_t$	28	0.455				93.87	1.043
2. $ln(N_t) = \alpha_t + \beta_t t + \epsilon_t$	26	0.468				99.36	1.045
3a. $ln(N_t) = \alpha + \beta_t ln(S_{t-1}) + \epsilon_t$	27	0.811				95.5	0.923
3b. $ln(N_t) = \alpha + \beta_t ln(N_{t-1}) + \epsilon_t$	27	1.005				91.82	1.031

Table S6. Table S5 with 1956-1982 data instead of 1983 to 2014 data. The years used in fit start in 1958 since $t-2$ (which is 1956 for the 1958 data point) is used in the covariates. See Table S4 for an explanation of the parameters and model set-up.

Model	Residual df	MASE	Adj. R2	F	p value	AIC	LOOCV
Time dependency test A 1958-1983 data							
1. $ln(N_t) = \alpha + \beta ln(S_{t-1}) + \epsilon_t$	24	0.658	-1.7			44.98	0.574
2. $ln(N_t) = \alpha + s(ln(S_{t-1})) + \epsilon_t$	22.1	0.548	16.2	3.53	0.052	41.11	0.542
3. $ln(N_t) = \alpha + s_1(ln(S_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	19.9	0.516	18.1	1.09	0.362	42	0.615
Time dependency test B 1958-1983 data							
1. $ln(N_t) = \alpha + \beta ln(N_{t-1}) + \epsilon_t$	24	0.699	-4.2			45.61	0.575
2. $ln(N_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	21.6	0.521	29.1	5.69	0.009	37.12	0.468
3. $ln(N_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(N_{t-2})) + \epsilon_t$	18.5	0.484	32.2	1.14	0.36	37.87	0.506
Time dependency test C 1958-1983 data							
1. $ln(N_t) = \alpha + s(ln(N_{t-1})) + \epsilon_t$	21.6	0.521	29.1			37.12	0.468
2a. $ln(N_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-1})) + \epsilon_t$	19	0.462	34.4	1.49	0.251	36.74	0.498
2b. $ln(N_t) = \alpha + s_1(ln(N_{t-1})) + s_2(ln(S_{t-2})) + \epsilon_t$	19.5	0.478	33.4	1.54	0.24	36.84	0.538

Tests for environmental variables as covariates

Table S7. Covariate tests for the October-March catch (N_t). M is the base model with prior season October-March catch (N_{t-1}) and July-September catch two seasons prior (S_{t-2}) as the covariates. To the base model, the environmental covariates are added. ns-SST is nearshore (0-80km) and r-SST is regional (0-160km) SST. Similarly, ns-Chl is nearshore chlorophyll. The nested F-tests are given in Supporting Information. The models are nested sets, e.g. 1, 2a, 3a and 1, 2b, 3b.

Model	Resid. df	Adj. R^2	RMSE	AICc	LOOCV RMSE	LOOCV MdAE
catch only models 1983-2014 data						
null model: $ln(N_t) = ln(N_{t-1}) + \epsilon_t$	32		0.999	92.9	0.999	0.256
base (M): 1. $ln(N_t) = \alpha + s(ln(N_{t-1})) + s(ln(S_{t-2})) + \epsilon_t$	26.6	57	0.7	84.6	1.055	0.345
Precipitation						
V_t = Jun-Jul Precipitation - satellite (S1)						
2a. $ln(N_t)$ = M + βV_t	25.7	58	0.685	86.5	1.083	0.365
3a. $ln(N_t)$ = M + $s(V_t)$	24.6	56	0.681	89.9	1.141	0.367
2b. $ln(N_t)$ = M + βV_{t-1}	25.6	56	0.7	87.9	1.066	0.375
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.5	58	0.669	89.1	1.058	0.347
V_t = Jun-Jul Precipitation - land gauges (S1)						
2a. $ln(N_t)$ = M + βV_t	25.7	63	0.638	81.9†	1.071	0.376
3a. $ln(N_t)$ = M + $s(V_t)$	24.6	70	0.56	77.5††	0.965‡	0.292‡‡
2b. $ln(N_t)$ = M + βV_{t-1}	25.7	56	0.701	87.8	1.081	0.346
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.7	55	0.691	90.5	1.088	0.331
V_t = Apr-May Precipitation - satellite (S2)						
2a. $ln(N_t)$ = M + βV_t	25.6	56	0.7	87.9	1.071	0.372
3a. $ln(N_t)$ = M + $s(V_t)$	24.4	54	0.694	92.1	1.098	0.477
2b. $ln(N_t)$ = M + βV_{t-1}	25.6	57	0.692	87.2	1.041	0.36
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.4	56	0.677	90.5	1.049	0.357
V_t = Apr-May Precipitation - land gauges (S2)						
2a. $ln(N_t)$ = M + βV_t	25.7	59	0.677	85.8	0.994‡	0.362
3a. $ln(N_t)$ = M + $s(V_t)$	23.8	58	0.66	91.2	0.998‡	0.475
2b. $ln(N_t)$ = M + βV_{t-1}	25.6	56	0.7	87.9	1.071	0.346
3b. $ln(N_t)$ = M + $s(V_{t-1})$	23.8	53	0.698	94.8	1.1	0.356
Sea surface temperature						
V_t = Mar-May r-SST (S5)						
2a. $ln(N_t)$ = M + βV_t	25.7	60	0.668	84.8	1.057	0.302‡‡
3a. $ln(N_t)$ = M + $s(V_t)$	24.4	64	0.614	84	0.999‡	0.366
2b. $ln(N_t)$ = M + βV_{t-1}	25.6	59	0.673	85.4	1.039	0.446
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.3	58	0.663	89.6	1.026	0.434
V_t = Oct-Dec ns-SST (L1)						
2a. $ln(N_t)$ = M + βV_t	25.7	59	0.674	85.4	1.138	0.358
3a. $ln(N_t)$ = M + $s(V_t)$	24.8	58	0.673	88.6	1.165	0.374
2b. $ln(N_t)$ = M + βV_{t-1}	25.7	56	0.701	87.9	1.077	0.298‡‡
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.8	57	0.681	89.4	1.132	0.394

Model	Resid. df	Adj. R^2	RMSE	AICc	LOOCV RMSE	LOOCV MdAE
Upwelling						
V_t = Jun-Sep SST-derived UPW (L2)						
2a. $ln(N_t)$ = M + βV_t	25.6	63	0.64	82.1†	1.005	0.536
3a. $ln(N_t)$ = M + $s(V_t)$	23.8	63	0.616	86.6	1.084	0.491
2b. $ln(N_t)$ = M + βV_{t-1}	25.6	56	0.7	87.9	1.104	0.321‡
3b. $ln(N_t)$ = M + $s(V_{t-1})$	23.9	57	0.665	91.4	1.186	0.37
V_t = Jun-Sep ns-SST (L2)						
2a. $ln(N_t)$ = M + βV_t	25.6	64	0.635	81.7†	1.029	0.414
3a. $ln(N_t)$ = M + $s(V_t)$	24.2	63	0.625	85.9	1.089	0.463
2b. $ln(N_t)$ = M + βV_{t-1}	25.7	56	0.698	87.7	1.083	0.432
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.2	55	0.683	91.7	1.114	0.51
V_t = Jun-Sep Bakun-UPW (L2)						
2a. $ln(N_t)$ = M + βV_t	25.6	58	0.682	86.2	1.036	0.391
3a. $ln(N_t)$ = M + $s(V_t)$	24.3	61	0.638	87.1	1.056	0.358
2b. $ln(N_t)$ = M + βV_{t-1}	25.7	58	0.684	86.4	1.015	0.423
3b. $ln(N_t)$ = M + $s(V_{t-1})$	24.4	59	0.66	88.7	1.081	0.44
Ocean climate						
V_t = 2.5-year average r-SST (A1)						
2a. $ln(N_t)$ = M + βV_t	25.7	66	0.615	79.6††	0.893‡‡	0.36
3a. $ln(N_t)$ = M + $s(V_t)$	24.7	72	0.546	75.6††	0.752‡‡‡	0.284‡‡
V_t = ONI (A2)						
2a. $ln(N_t)$ = M + βV_t	25.7	57	0.693	87	1.022	0.51
3a. $ln(N_t)$ = M + $s(V_t)$	25.1	57	0.683	88.2	1.072	0.461
V_t = Sep-Nov DMI (A3)						
2a. $ln(N_t)$ = M + βV_t	25.7	56	0.696	87.3	1.09	0.329
3a. $ln(N_t)$ = M + $s(V_t)$	23.6	58	0.657	91.6	1.2	0.369
2b. $ln(N_t)$ = M + βV_{t-1}	25.7	56	0.702	87.9	1.076	0.333
3b. $ln(N_t)$ = M + $s(V_{t-1})$	23.8	69	0.565	81.3†	0.876‡‡	0.348
V_t = DMI 2.5-year average (A3)						
2a. $ln(N_t)$ = M + βV_t	25.7	61	0.657	83.7	0.946‡‡	0.433
3a. $ln(N_t)$ = M + $s(V_t)$	24.9	62	0.637	84.5	0.932‡‡	0.433
catch only models 1958-1989 data						
null model: $ln(N_t) = ln(N_{t-1}) + \epsilon_t$	32		0.804	79	0.804	0.398
base (M): 1. $ln(N_t) = \alpha + s(ln(N_{t-1})) + s(ln(S_{t-2})) + \epsilon_t$	26.8	15	0.604	74.7	0.913	0.423
Select covariates available from 1957						
V_t = Jun-Jul Precipitation - land gauges (S1)						
2a. $ln(N_t)$ = M + βV_t	25.8	12	0.604	78	0.95	0.456
3a. $ln(N_t)$ = M + $s(V_t)$	24.3	18	0.566	79.4	0.946	0.555

Model	Resid. df	Adj. R^2	RMSE	AICc	LOOCV RMSE	LOOCV MdAE
V_t = Sep-Nov DMI (A3)						
2a. $ln(N_t)$ = M + βV_{t-1}	25.8	17	0.588	76.2	0.902	0.447
3a. $ln(N_t)$ = M + $s(V_{t-1})$	24.1	21	0.553	78.6	0.906	0.4‡
catch only models 1998-2014 data						
null model: $ln(N_t) = ln(N_{t-1}) + \epsilon_t$	17		0.432	22	0.432	0.133
base (M): 1. $ln(N_t) = \alpha + p(ln(N_{t-1})) + \epsilon_t$	14	27	0.334	22.3	0.422	0.369
Chlorophyll						
V_t = Jul-Sep ns-CHL (L3)						
2a. $ln(N_t)$ = M + βV_t	13	24	0.327	25.7	0.441	0.344‡
3a. $ln(N_t)$ = M + $p(V_t)$	12	19	0.325	30.5	0.496	0.333‡
2b. $ln(N_t)$ = M + βV_{t-1}	13	31	0.311	24	0.418	0.348‡
3b. $ln(N_t)$ = M + $p(V_{t-1})$	12	26	0.311	28.9	1.616	0.362
V_t = Oct-Dec ns-CHL (L3)						
2a. $ln(N_t)$ = M + βV_t	13	24	0.327	25.7	0.445	0.336‡
3a. $ln(N_t)$ = M + $p(V_t)$	12	35	0.29	26.6	0.391‡	0.217‡‡‡
2b. $ln(N_t)$ = M + βV_{t-1}	13	45	0.277	20.1†	0.364‡‡	0.235‡‡‡
3b. $ln(N_t)$ = M + $p(V_{t-1})$	12	41	0.277	25.1	0.384‡	0.278‡‡‡

Notes: LOOCV = Leave one out cross-validation. RMSE = root mean square error, AICc = Akaike Information Criterion corrected for small sample size. † = AIC greater than 2 below model M (base catch model). †† = AIC greater than 5 below model M. ‡ = LOOCV RMSE 5% below model M. ‡‡ = LOOCV RMSE 10% below model M. t indicates current season (Jul-Jun) and $t-1$ is prior season. Thus a Jan-Mar covariate with $t-1$ would be in the same calendar year as the Jul-Sep catch, though in a prior fishing season. With the exception that for covariates that are calendar year (Jan-Dec) or multiyear, t is the current calendar year.

Validation of catch base models

Test set-up

This describes a variety of cross-validations used to select the base model for landing. The base model is the model with no environmental covariates only prior landings as covariates.

Three types of base models were fit. The first two were GAM and linear models with Jul-Sep and Oct-Mar in the prior season only or prior season and two seasons prior as covariates. c is the response variable: landings during the two seasons, either Jul-Sep or Oct-Mar.

$$\begin{aligned}
\text{GAM t-1} : X_t &= \alpha + s(c_{t-1}) + e_t \\
\text{Linear t-1} : X_t &= \alpha + \beta c_{t-1} + e_t \\
\text{GAM t-1, t-2} : X_t &= \alpha + s(c_{t-1}) + s(d_{t-2}) + e_t \\
\text{Linear t-1, t-2} : X_t &= \alpha + \beta c_{t-1} + d_{t-2} + e_t
\end{aligned}$$

where c_{t-1} was either S_{t-1} (Jul-Sep landings in prior season) or N_{t-1} (Oct-Mar landings in prior season) and d_{t-2} was the same but 2 seasons prior.

These types of models do not allow the model parameters (the intercept α and effect parameter β) to vary in time. The second type of models were dynamic linear models (DLMs). DLMs allow the parameters to evolve in time. Two types of DLMs were used, an intercept only model where the intercept α evolves and a linear model where the effect parameter β is allowed to evolve:

$$\begin{aligned}
\text{DLM intercept only} : X_t &= \alpha_t + e_t \\
\text{DLM intercept and slope} : X_t &= \alpha_t + \beta_t t + e_t \\
\text{DLM intercept and effect} : X_t &= \alpha + \beta_t c_{t-1} + e_t
\end{aligned}$$

In addition to the GAM, linear and DLM models, three null models were included in the tested model sets:

$$\begin{aligned}
\text{intercept only} : X_t &= \alpha + e_t \\
\text{intercept and prior catch} : X_t &= \alpha_t + X_{t-1} + e_t \\
\text{prior catch only} : X_t &= X_{t-1} + e_t
\end{aligned}$$

The 'intercept only' is a flat level model. The 'prior catch only' simply uses the prior value of the time series (in this case landings) as the prediction and is a standard null model for prediction. The 'intercept and prior catch' combines these two null models.

The models were fit to the 1956-2015 landings (full data) and 1984-2015 (data that overlap the environmental covariates).

The model performance was measured by AIC, AICc and LOOCV prediction. The LOOCV prediction error is the data point t minus the predited value for data point t. This is repeated for all data points t. The influence of single data points to on model performance was evaluated by leaving out one data point, fitting to the remaining data and computing the model performance (via AIC, AICc or LOO prediction error).

Results: Jul-Sep landings

The Figure S1 shows the ΔAIC for the models: GAM, linear, and DLM. The figure shows that for the 1984-2015 data with any year left out, the set of models that has the lowest AIC was always the GAM or linear model with Oct-Mar in the prior season. There were cases where deleting a year removed one of these two from the 'best' category, but they were still in the 'competitive' category with a ΔAIC less than 2.

AIC gives us a measure of how well the models fit the data, with a penalty for the number of estimated parameters. We look at the one-step-ahead predictive performance (Figure S2), we see that all the GAM, linear and DLM models have a hard time adjusting to shifts in the data (e.g. after 1998). The null models can adjust quickly but has large errors when there are rapid changes. The leave one out predictive error (the root mean squared error which penalizes large predictive errors) is lowest for the models with Oct-Mar in the prior season (Figure S3).

It should be noted that none of the Jul-Sep models has a particularly high adjusted R^2. The values are generally less than 0.3. The Jul-Sep landings tend to be highly variable and not related to the catch in prior years. Jul-Sep is during the monsoon during which fishing is not always possible due to sea-state and there is a 6-week fishing ban during this time.

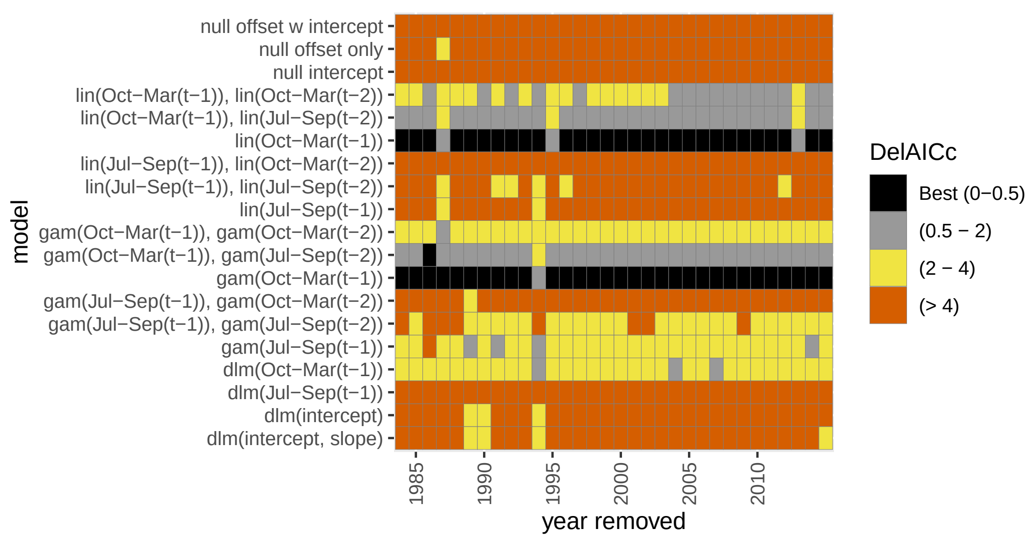

Figure S1. ΔAICc for the Jul-Sep landings base models with one year deleted using only the landings data that overlap with the environmental data 1984-2015.

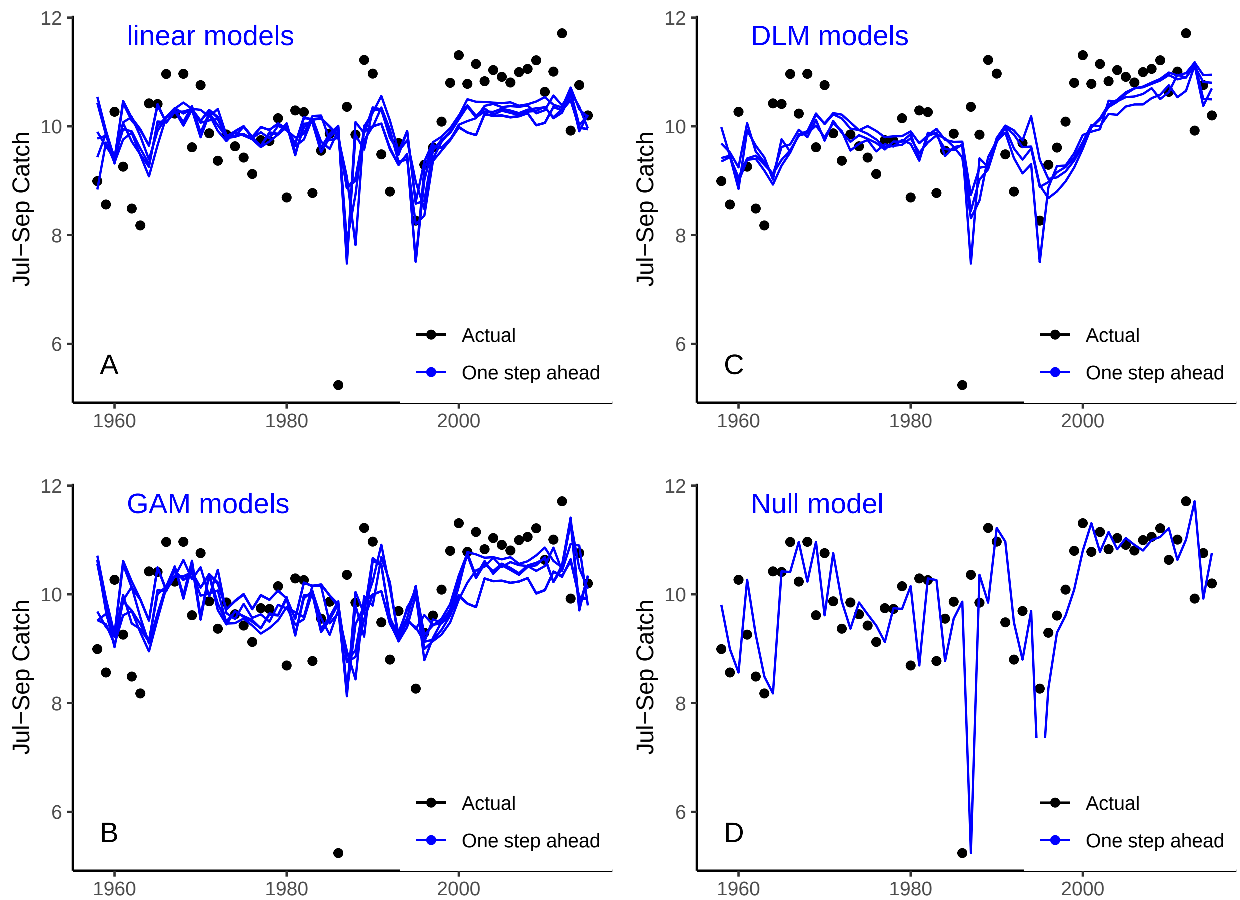

Figure S2. Leave one out (LOO) one step ahead predictions for the linear, GAM, and DLM models of Jul-Sep landings. The data point at year t on the x-axis is predicted from the data up to year t-1.

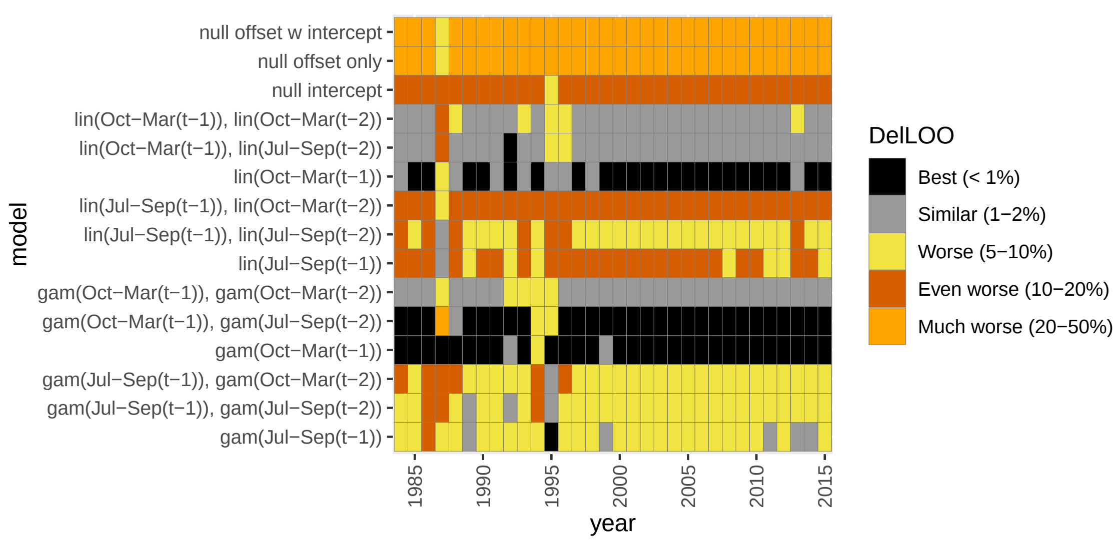

Figure S3. Leave-one-out predictive performance (leave out a year, fit, predict that year) for the Jul-Sep landings base models. The performance (DelLOO) is the RSME (root mean square error) between prediction and observed.

Validation of the Oct-Mar landings base models

Figure S4 shows that for Oct-Mar landings with the 1984 to 2015 data, the best model was always GAM with Oct-Mar in the prior season and Jul-Sep landings two seasons prior. For the one step ahead predictions, a simpler models had the lower prediction errors: GAM with Oct-Mar in the prior season as the only covariate (Figure S5).

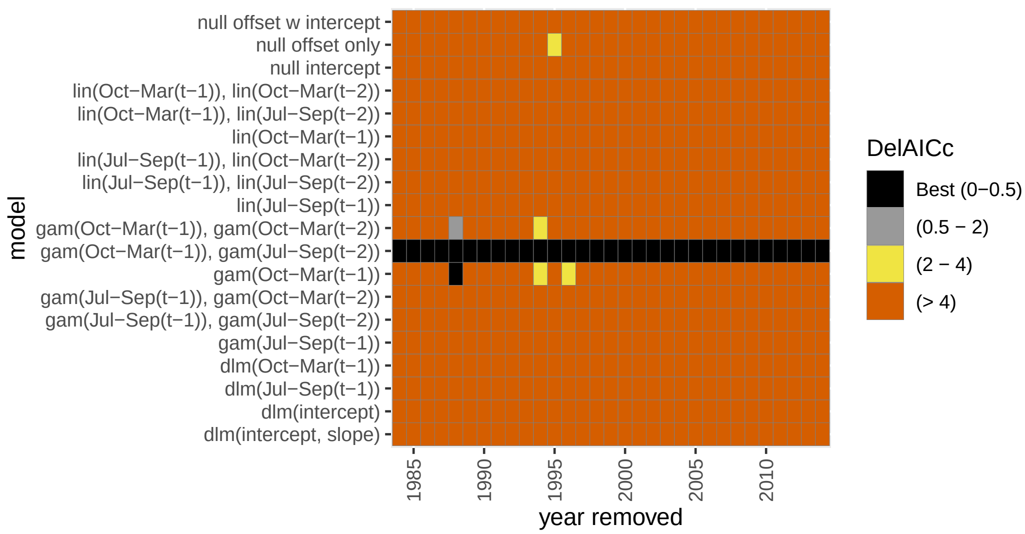

Figure S4. ΔAICc for the Oct-Mar landings base models with one year deleted using only the landings data that overlap with the environmental data 1984-2015. See Figure S1 for an explantion of the figure.

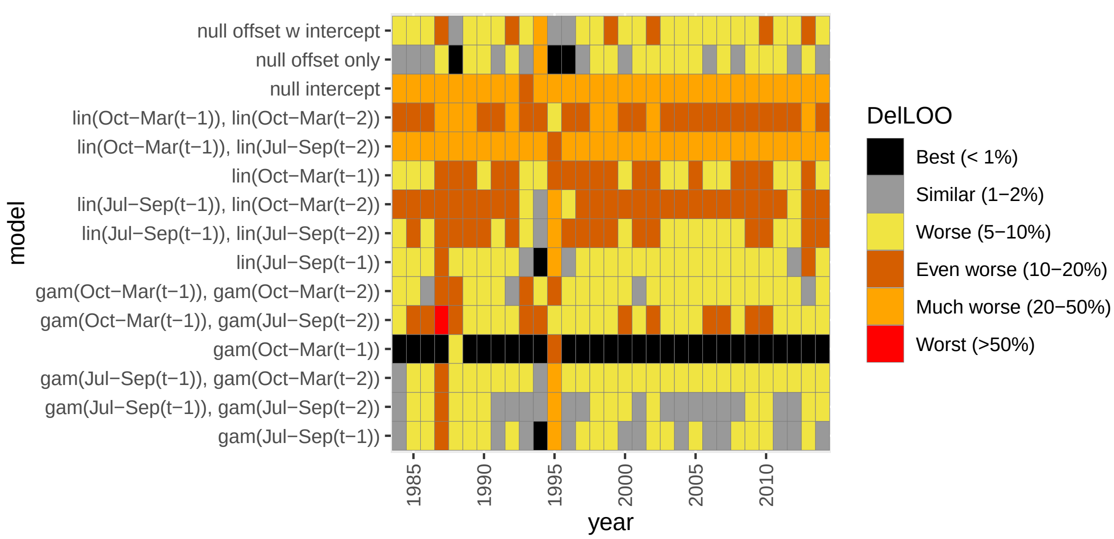

Figure S5. Leave-one-out predictive performance (leave out a year, fit, predict that year) for the Oct-Mar landings base models. The performance (DelLOO) is the RSME (root mean square error).

Comparison of land and oceanic rainfall measurements

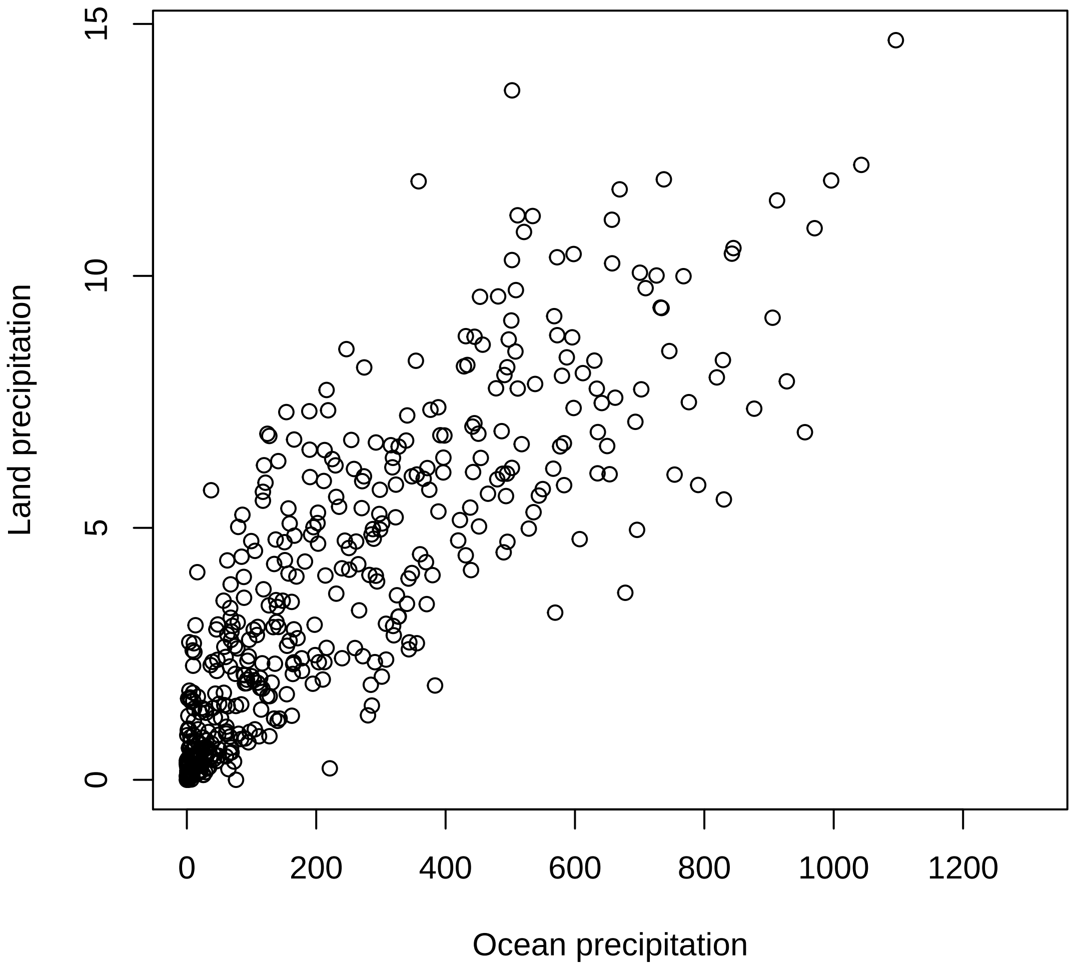

Figure S6. Monthly precipitation measured over land via land gauges versus the precipitation measured via remote sensing over the ocean.