Evaluation of generalized depletion modeling of the US *Illex* fishery

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SSC meeting: 05-10-2022

ICES Journal of Marine Science

ICES CIEM International Co[…] the Exploration […] Conseil Internati[…] l'Exploration de l[…]

ICES Journal of Marine Science (2020), doi:10.1093/icesjms/fsaa038

Review article

Contribution to the Symposium: '*Johan Hjort Symposium 2019*'

Stock assessment and management of cephalopods: advances and challenges for short-lived fishery resources

Alexander I. Arkhipkin [1]*, Lisa C. Hendrickson [2], Ignacio Payá[3], Graham J. Pierce[4,5], Ruben H. Roa-Ureta[6], Jean-Paul Robin[7], and Andreas Winter[1]

Cephalopods:

- Fast population dynamics & weak S-R relationships
- fishery independent survey data rarely comprehensive
- aging expensive & time consuming
- age-based assessment impractical

"Best methods…….
… innovative depletion models fitted with in-season data"

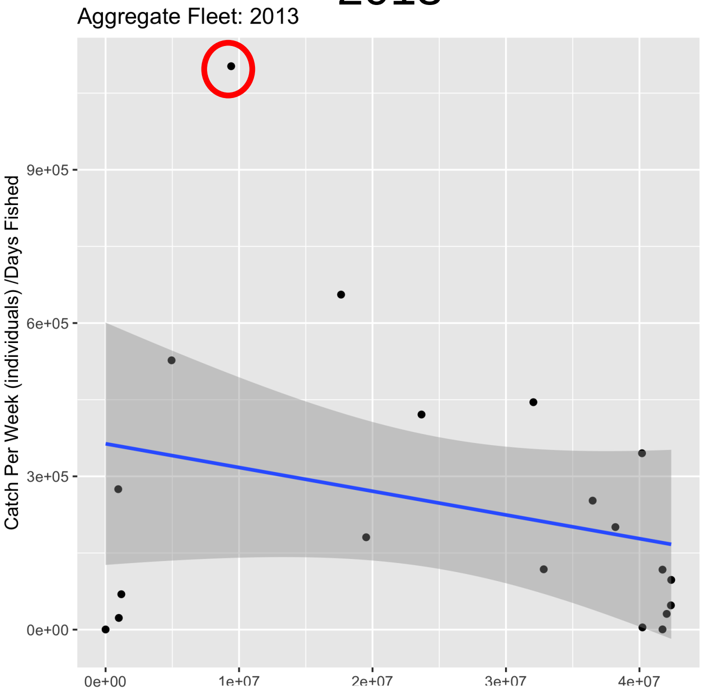
Arkhipkin et al. 2020

Classical Leslie-Davis modeling applied to Illex fishery

Rago 2020: CPUE decreased continuously in only 4 of 19 years as expected if fishery closed to in-season migration

2013

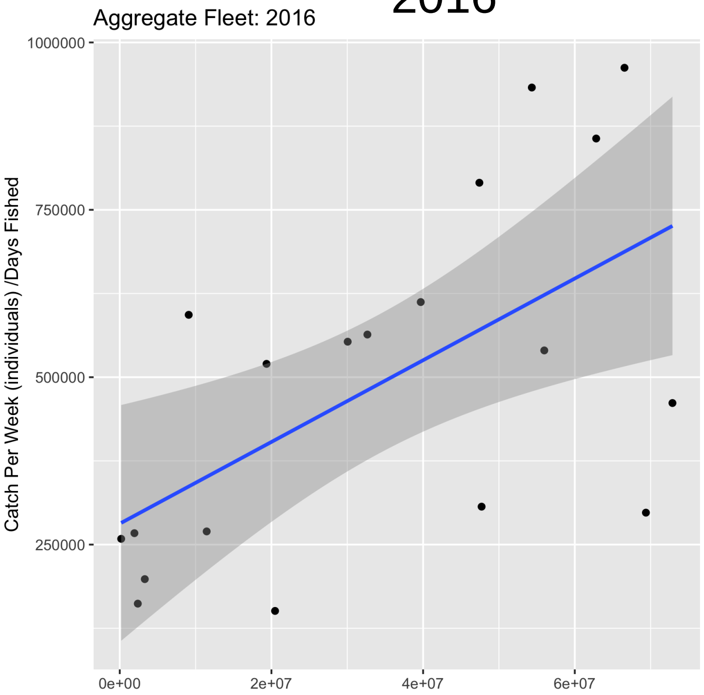
LPUE



Cumulative Landings

2016

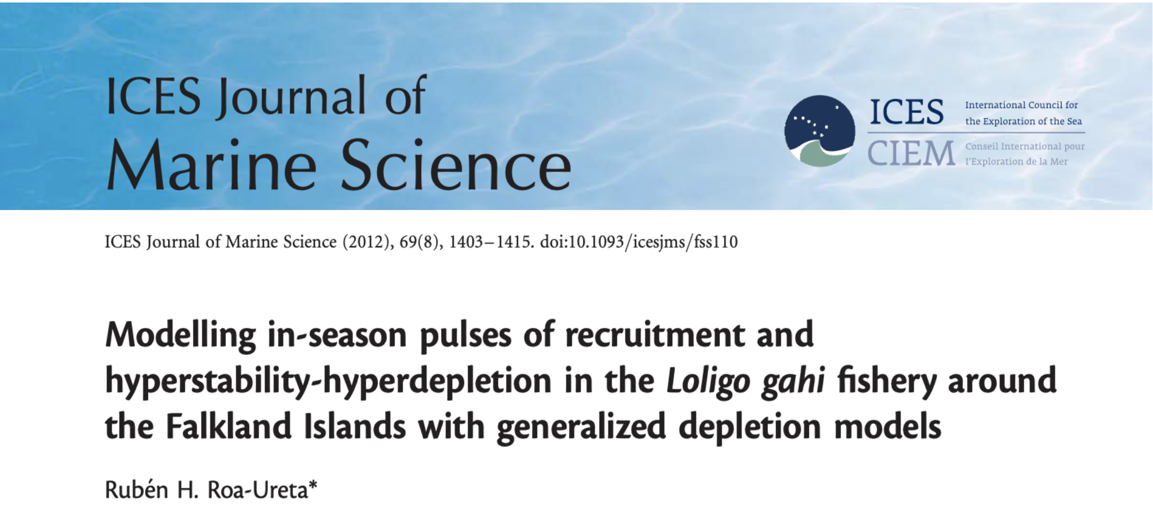
LPUE



Cumulative Landings

Generalized depletion modeling

Accounts for in-season migration & complex catch-population size relationships


ICES Journal of Marine Science

ICES CIEM International Council for the Exploration of the Sea / Conseil International pour l'Exploration de la Mer

ICES Journal of Marine Science (2012), 69(8), 1403–1415. doi:10.1093/icesjms/fss110

Modelling in-season pulses of recruitment and hyperstability-hyperdepletion in the *Loligo gahi* fishery around the Falkland Islands with generalized depletion models

Rubén H. Roa-Ureta*

Requires high frequency records

(daily, weekly)

- catch biomass
- effort
- representative individual weights of catch *(to convert catch biomass to number)*

Selected references:

Roa-Ureta, R.H., 2015. Stock assessment of the Spanish mackerel *(Scomberomorus commerson)* in Saudi waters of the Arabian Gulf with generalized depletion models under data-limited conditions. Fisheries Research 171 (2015) 68–77

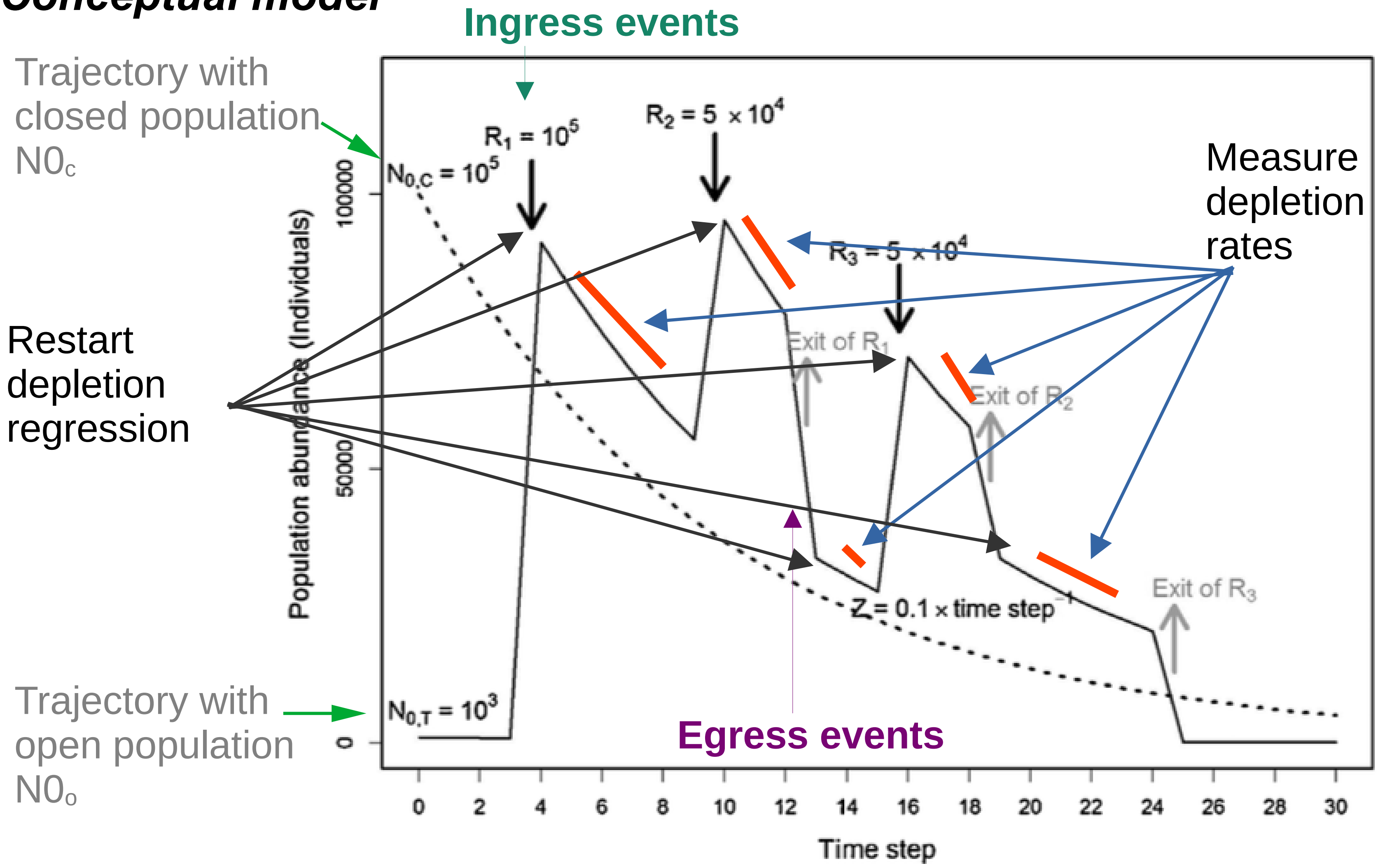
Lin, Y.-J. et. al. 2017. A stock assessment model for transit stock fisheries with explicit immigration and emigration dynamics: application to upstream waves of glass eels. Fisheries Research 195, 130–140.

Maynou, F. et. al 2021 Application of a multi-annual generalized depletion model to the Mediterranean sand eel fishery in Catalonia. Fisheries Research 234: 105814

Roa-Ureta, et al 2021, Estimation of the spawning stock and recruitment relationship of *Octopus vulgaris* in Asturias (Bay of Biscay) with generalized depletion models: implications for the applicability of MSY. ICES Journal of Marine Science, 78(6) 2256–2270

Generalized depletion modeling: *with open population assumption*

Conceptual model



From Lin et al. 2017

Generalized depletion modeling: Permits nonlinear catchability

$$C_t = \boxed{k E^{\alpha}_{t} N^{\beta}_{t}} e^{-M/2}$$

C_t = Estimated catch in number at time t
E_t = Fishing effort at time t
N_t = Latent abundance of vulnerable fraction of population at time t
M = natural mortality at time step

k = a scaler (similar to q)
α = effort response.
- α < 1 (saturable. gear catches proportionally less with additional effort),
- α ~ 1 (catch proportional to effort)
- α > 1 (synergistic. Disproportionate increase in catch with effort increase)

β abundance response (fishers perception of true population abundance)
- β<1 (hyperstability. stable catch when population abundance declines)
- β=1 (Proportionality. catch tracks population abundance)
- β >1 (hyperdepletion. catch rate declines faster than population abundance)

Multiple fleets in a fishery can be modeled if k,α, and/or β sufficiently different

GDM parameter estimates

- Population: N_0 & M wk^{-1}
- Fleet specific:
  - catchability (k, α, β)
  - Migration events (P_{mag}, Timing)

GDM requires:

- sound inferences in-season migration timing & magnitude
- allot of data (to produce reasonable param/data ratios)
-1 fleet model w/ 1 ingress event = 7 parameters

Assumptions of classical depletion modeling

relaxed in GDM

1) Population vulnerable to fishery physically & demographically closed

2) Natural mortality (M) constant

3) Catch linearly related to population abundance by scaler q

4) Catchability constant over fishing period & a large pool of animals does not have a refuge & q~0

5) Units of fishing effort are independent & do not compete

6) Fishing capacity is large enough that depletion can be detected & parameters estimated

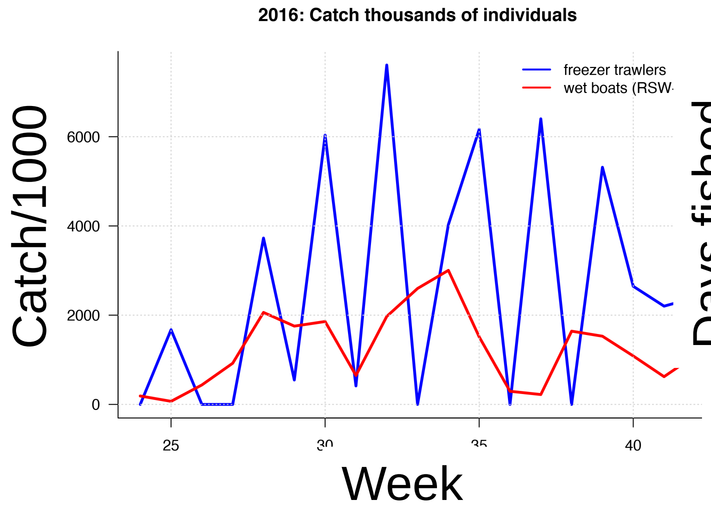
7) The assumptions of linear regression

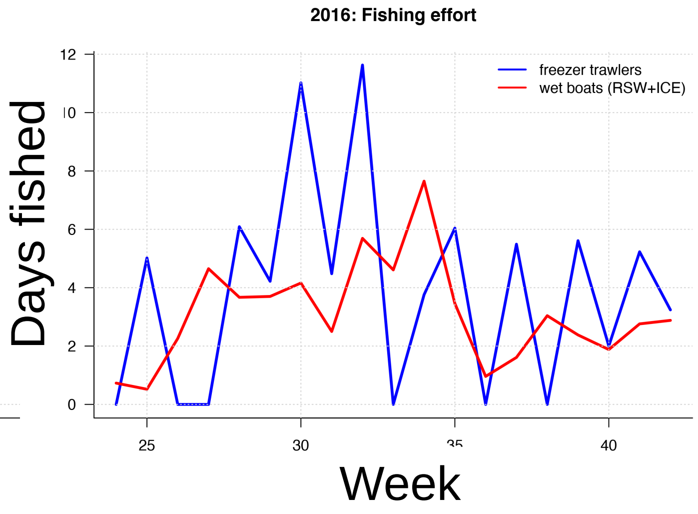
Generalized depletion modeling: 2016 Illex season

Data: Weekly landings & industry weigh-out data

								Fishery condition			
Year	Date Start	Start Week	End Week	Closure (Wk)	N weeks	Total Catch	% in Data	Industry	Statistical	#Vessels landing>50k	Days Fished
2013	06-10	24	37		14	4,107,000	81	Poor	Poor	12	75
2016	06-13	24	42		19	7,004,000	90	Poor	Poor	10	133
2017	05-02	22	37	37	16	23,371,000	100	Good	Good	20	149
2018	05-28	22	33	33	12	25,524,000	97	Good	Good	26	188
2019	05-02	21	34	34	14	28,495,000	94	Good	Good	32	338

2016 Freezer trawler fleet: 68% of catch & 55% effort





GDM development strategy

Step 1: MLE Fit pure depletion GDM w/ closed population assumption.
Select “best” H0 model variant

Step 2: Develop hypotheses for open population GDMs.

Step 3: Fit GDM reflecting open population hypotheses
& select “best” variants

Step 4: Select “best” hypothesis from H0….Hn

Step 5: Use “best” hypothesis model variant to develop parameter
estimates & derived quantities

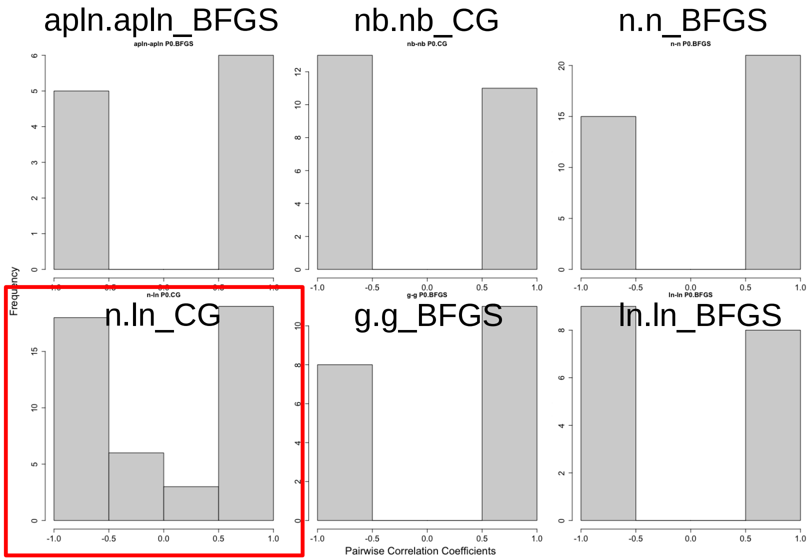
2016 Generalized depletion modeling

H0. Pure depletion model w/closed population assumption

Of 48 models specified
7 converged with |param gradients| < 1 & fewer than 2 SE NAs

Distribution	Method	Max.Abs.Grads.	M	M_%CV	N0	N0_%CV	SE_Nas
aplnormal,aplnormal	BFGS	0.08	0.00001	4148.4156	289,232,685	46	0
negbin,negbin	CG	0.02	0.00015	2153.72601	29,821,419	2225	0
normal,normal	BFGS	0.07	0.00000	8958.41323	6,929,326,679	NA	1
lognormal,normal	CG	0.20	0.00138	438.812067	4,179,970	57	2
normal,lognormal	CG	0.15	0.00033	461.892935	17,968,406	90	2
lognormal,lognormal	BFGS	0.14	0.00003	1978.01903	180,676,740	2027	2
gamma,gamma	BFGS	0.05	0.00004	4559.80348	520,690,210	NA	2

Parameter
Correlations



Biological realism
- M low by orders of magnitude
- suggests squid ingress

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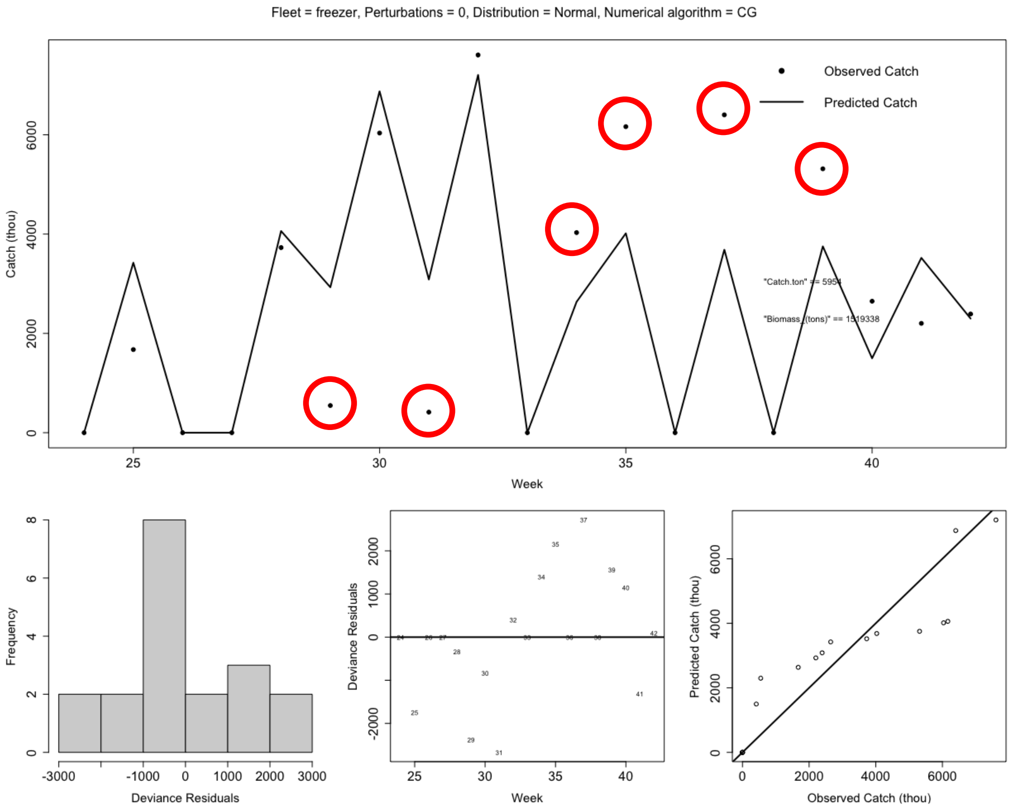
Catch perturbation analysis

2016: Residuals of (H0) pure depletion model

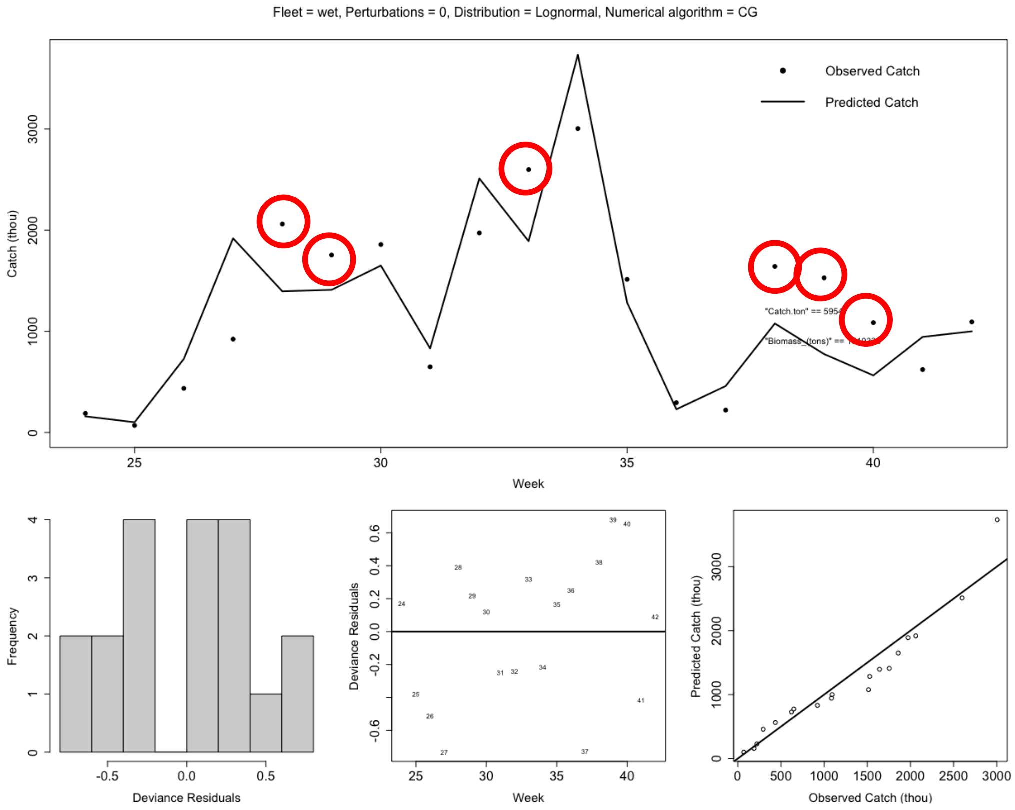
illill.2016_F2P0.0.n.ln.fit.pred.CG

Used primarily for open population hypothesis development

Freezer trawlers

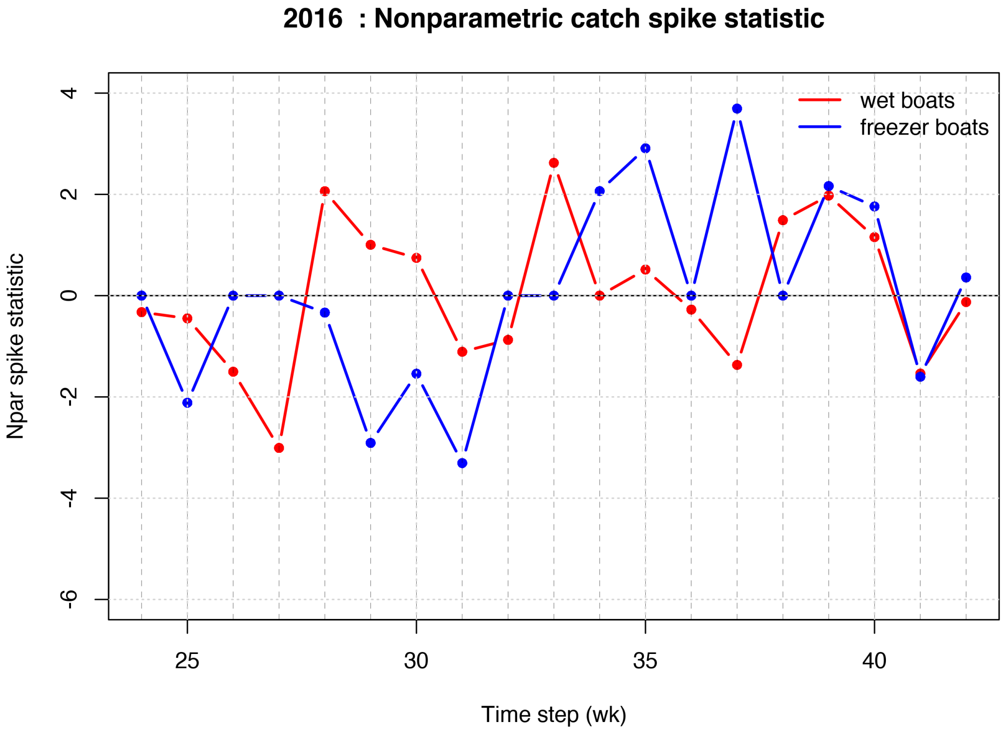


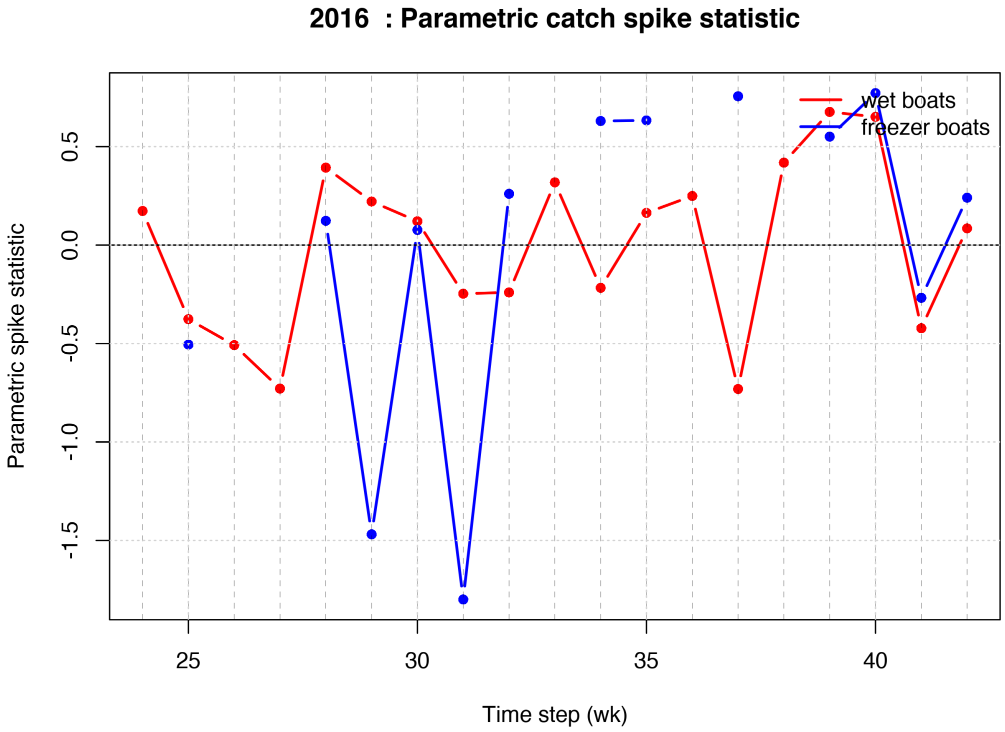
Wet boats (RSW + ICE)



Catch perturbation analysis

***2016: Catch spike statistics.** Anomalies in catch standardized by effort*



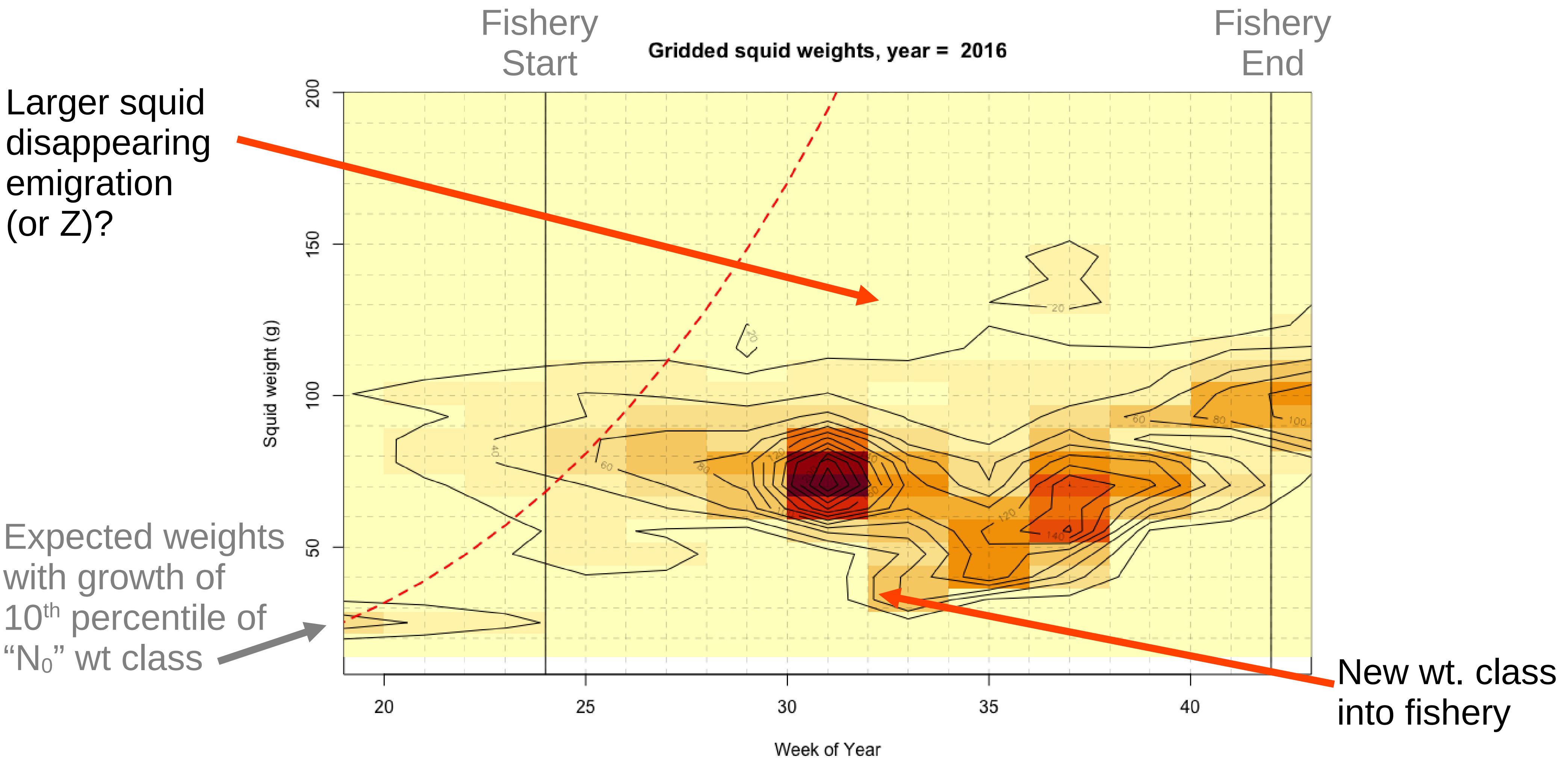


Freezer week: 25-, 29-,31-, 35+, 37+,39+
Wet week: 25-, 27-, 29+, 33+, 37-, 39+

Freezer week: 29-, 31-,34+, 35+, 37+, 39+, 40+
Wet week: 27-, 28+, 33+, 37-, 38+,39+

Catch perturbation analysis

2016: Weight frequencies from industry data

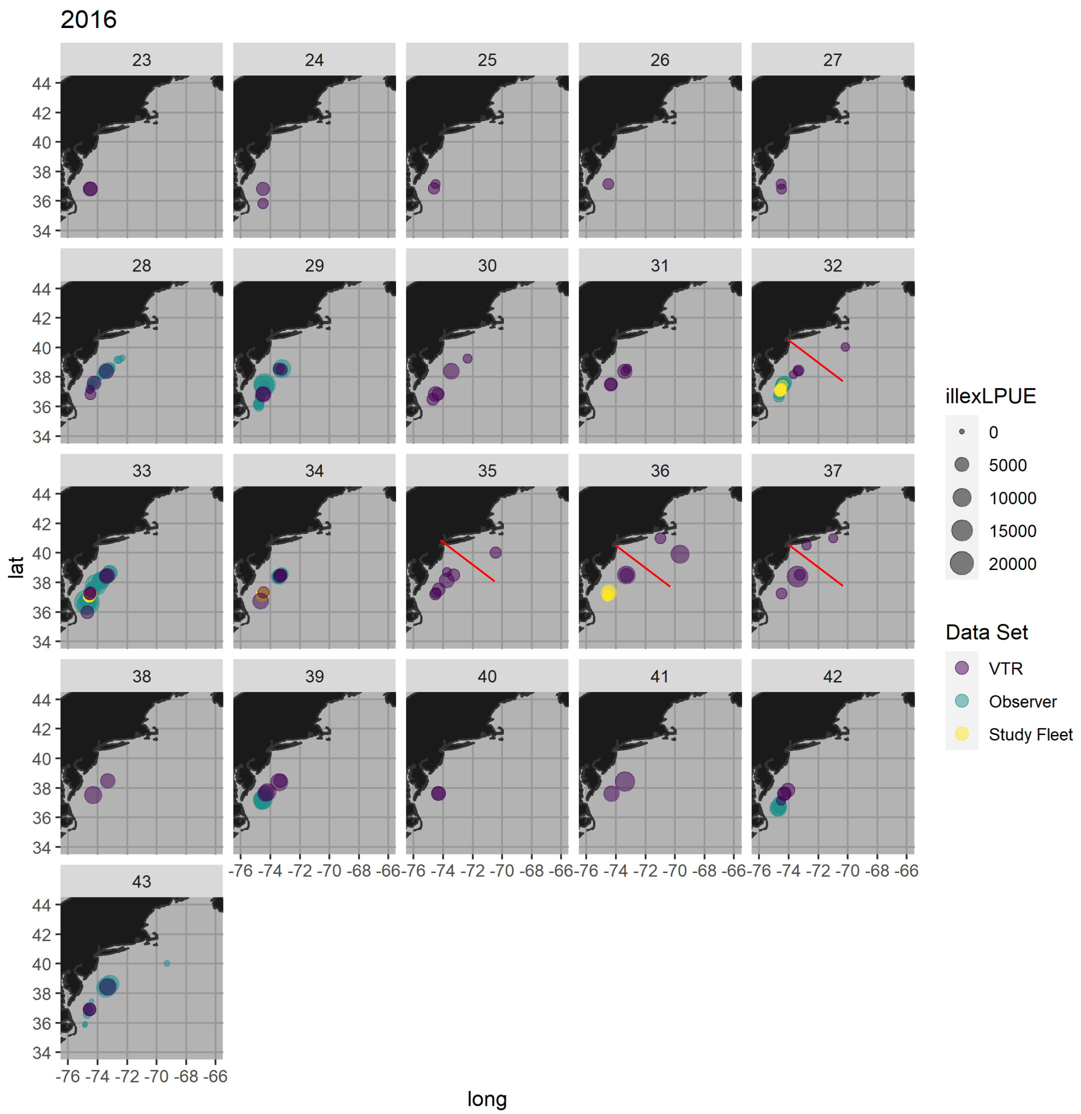


Catch perturbation analysis

2016: Fleet dynamics

Catch relative to Hudson Self Valley
Persistent catch SW all weeks
Weeks 23-31, 33-34, 38-43

Some catch NE weeks 32, 35-37



Catch perturbation analysis

2016: Perturbation summary table

			Freezer		Catch spikes		Wet		Catch spikes			
Week	Fleet Dyn	Wt. Freq	DF	H0_resid	N Par	Par	DF	H0_resid	N Par	Par	Hypothesis	Timings Wk
24	SW		0				0.73					
25	SW		5.02		-		0.52					
26	SW		0				2.26					E1.wet= -27
27	SW		0				4.65		-	-		E1.freeze= -29
28	SW		6.09				3.67	+	+	+	H3: P1E1P2E1	P1.wet=33
29	SW		4.22	-	-	-	3.7					P1.freeze=34
30	SW	+	11.02				4.16					P2.wet=38
31	SW		4.48	-	-	-	2.5					
32	SW & NE	+	11.63				5.69					
33	SW		0				4.61		+	+	H1: P1P1	P1.wet=33
34	SW	+	3.76	+		+	7.65	-				P1.freeze=34
35	SW & NE	+	6.04	+	+	+	3.46					
36	SW & NE		0				0.96					
37	SW & NE		5.49	+	+	+	1.61	+		-		
38	SW		0				3.04	+		+		
39	SW		5.61		+	+	2.38	+	+	+	H2: P2P2	P1.wet=33
40	SW		2			+	1.88	+		+		P1.freeze=34
41	SW		5.23				2.76					P2.freeze=37
42	SW		3.24				2.88					P2.wet=38
		Total	73.8				59.1					
		# Effort	56				44					

GDM development strategy

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2016 Generalized depletion modeling

Parameter estimates of "best" model variants for H1 & H2a,b. (H3 variants fail criteria)

H0:

Best H0 variant 2016. P0P0 normal, alognormal_CG						
Parameter	Timing.freezer	Estimates.freezer	CVpCent.freezer	Timing.wet	Estimates.wet	CVpCent.wet
M.1/week		0.0003	462		0.0003	462
N0.thou		17,968,406	90		17,968,406	90
k.1/Days Fished		0.0001	NA		0.0001	5714
alpha		1	25		1	11
beta		0.95044	NA		0.91990	371
psi.thou.squared		1910874.32	33		0.18	33

Produced SEs
Most CV < 100
M Reasonable
Parsimonious

H1:
P1.freezer ← +34
P1.wet ← +33

Best H1 variant 2016. P1P1 aplognormal, aplognormal_BFGS						
Parameter	Timing.freezer	Estimates.freezer	CVpCent.freezer	Timing.wet	Estimates.wet	CVpCent.wet
M.1/week		0.026	57		0.026	57
N0.thou		26,221,404	7		26,221,404	7
Rec.thou.Wave1	08-28_09-03	90,828	5657	08-14_08-20	37,092,712	22
k.1/Days Fished		0	8		2	168
alpha		1.61655	3		1.33916	11
beta		1.67	1		0.29	33

H2:
P1.freezer ← +34
P1.wet ← +33
P2.freezer ← +37
P3.wet ← +38

Best H2 variant 2016. P2P2 normal,normal_CG						
Parameter	Timing.freezer	Estimates.freezer	CVpCent.freezer	Timing.wet	Estimates.wet	CVpCent.wet
M.1/week		0.006	309		0.006	309
N0.thou		448,208	185		448,208	185
Rec.thou.Wave1	08-14_08-20	149,517	NA	08-14_08-20	39,457	NA
Rec.thou.Wave2	09-11_09-17	34,734	1025	09-11_09-17	18,546	1887
k.1/Days Fished		0.00003	416		0.00016	858
alpha		0.81	25		0.91	20
beta		1.31	27		1.13	25
psi.thou.squared		1131468	37		191868.52	35

Most CV < 100
M Reasonable
Missing SEs
Less Parsimony

H2b:
P1.freezer ← +34
P1.wet ← +33

P3.wet ← +38

Best 2016 H2b variant. P1P2 normal, lognormal_ CG.						
Parameter	Timing.freezer	Estimates.freezer	CVpCent.freezer	Timing.wet	Estimates.wet	CVpCent.wet
M.1/week		0.013	246		0.013	246
N0.thou		74,581	84		74,581	84
Rec.thou.Wave1	08-28_09-03	56,559	74	08-28_09-03	21,964	84
Rec.thou.Wave2				08-14_08-20	16,036	91
k.1/Days Fished		0.00002	168		0.00036	NA
alpha		1.28	14		1.42	12
beta		1.51	16		1.19	NA
psi.thou.squared		502500	41		0.23	21

2016 Generalized depletion modeling

"Best" hypothesis (P1P1) & model variant (apln.apln.BFGS)

Choice based upon

a) numerical, statistical, biological realism criteria

b) confirmed using AIC & variants with same distribution assumptions

Best H1 variant 2016. P1P1 aplognormal, aplognormal_BFGS						
Parameter	Timing.freezer	Estimates.freezer	CVpCent.freezer	Timing.wet	Estimates.wet	CVpCent.wet
M.1/week		0.026	57		0.026	57
N0.thou		26,221,404	7		26,221,404	7
Rec.thou.Wave1	08-28_09-03	90,828	5657	08-14_08-20	37,092,712	22
k.1/Days Fished		0	8		2	168
alpha		1.61655	3		1.33916	11
beta		1.67	1		0.29	33

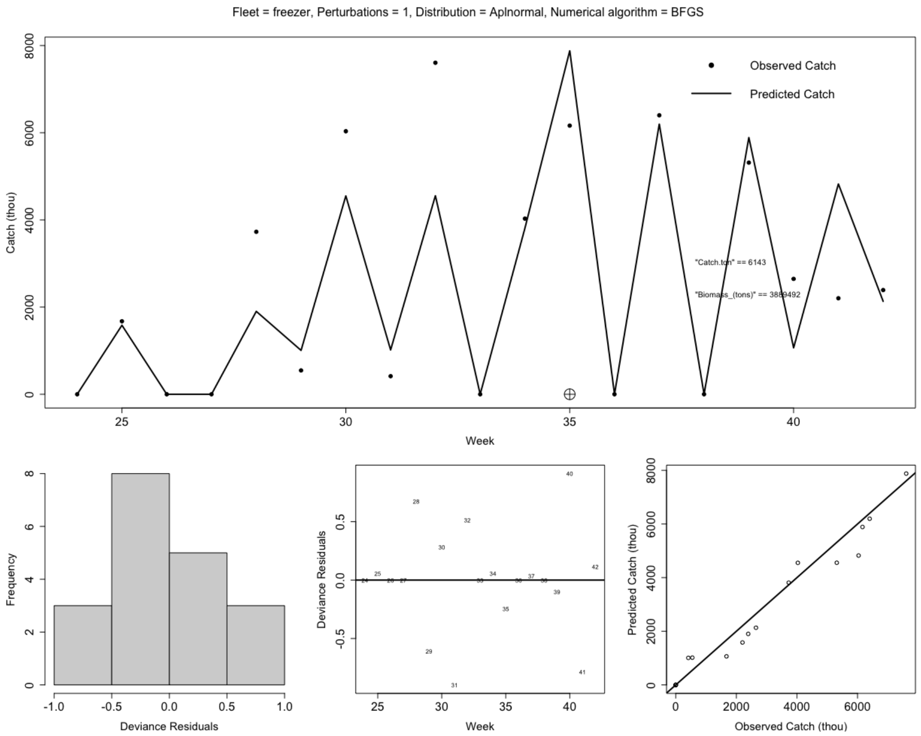
% CV > 100

2016 Generalized depletion modeling

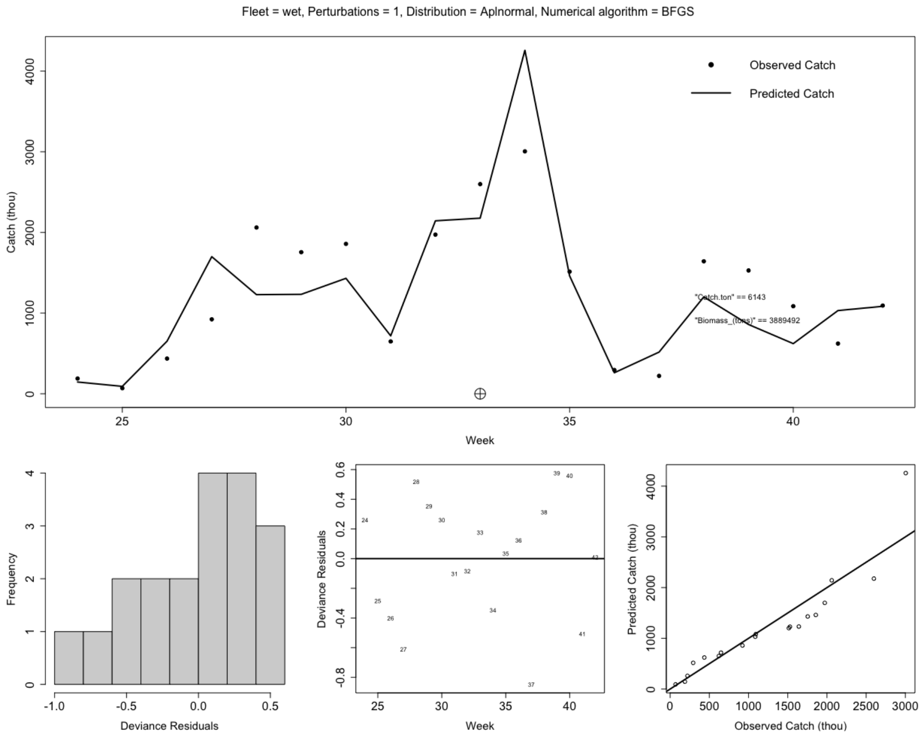
Model fit for "best" H1 model variant
illill.2016_F2P1E0P1E0.0.apln.apln.pred.BFGS

In-season pulses : 08-28_09-03 | 08-14_08-20

Freezer trawlers



Wet boats (RSW + ICE)



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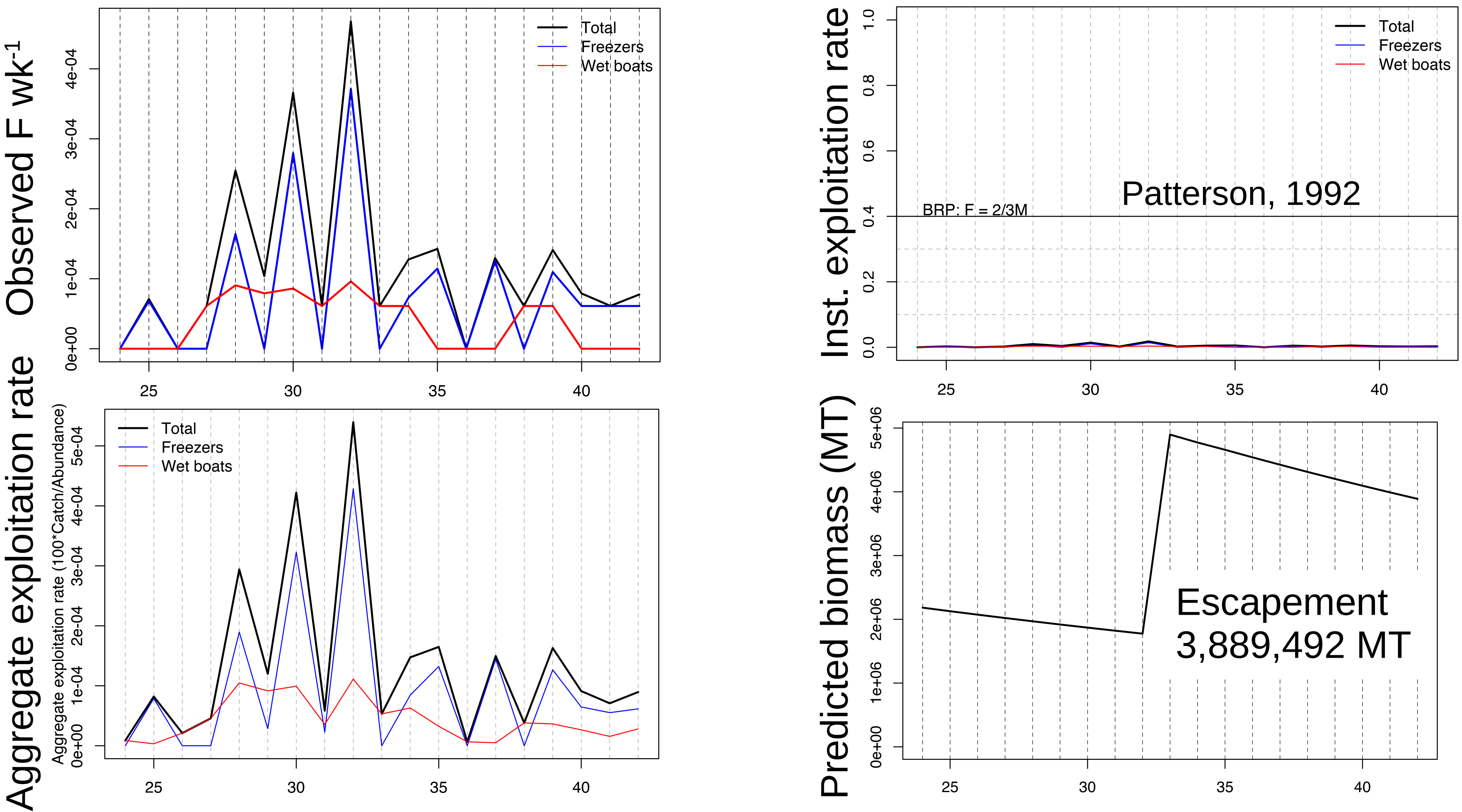
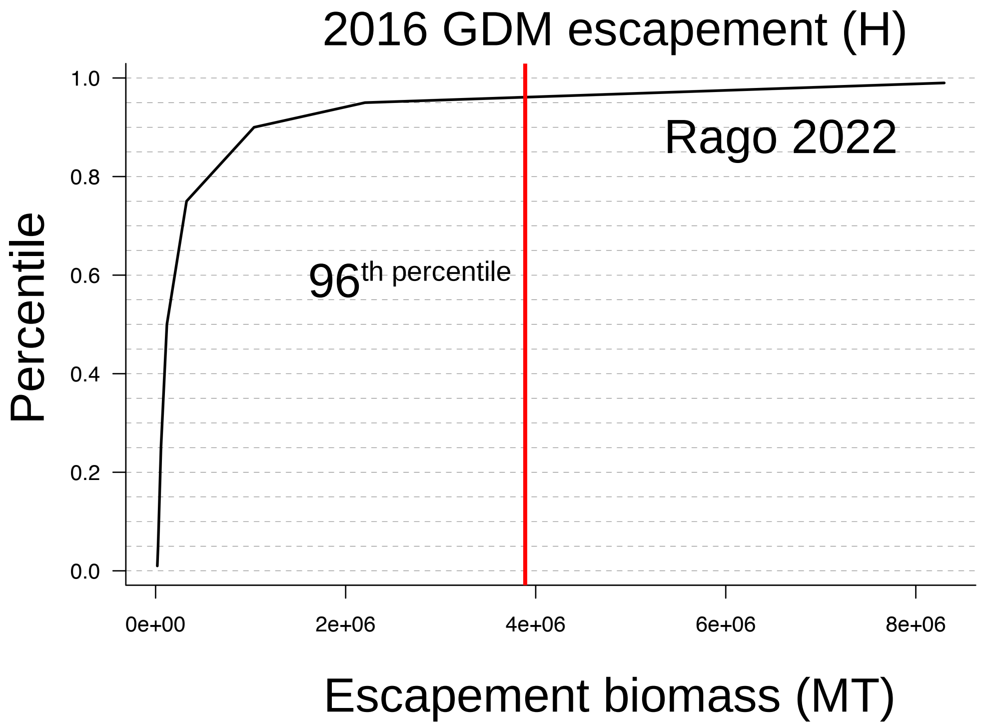
2016 Generalized depletion modeling

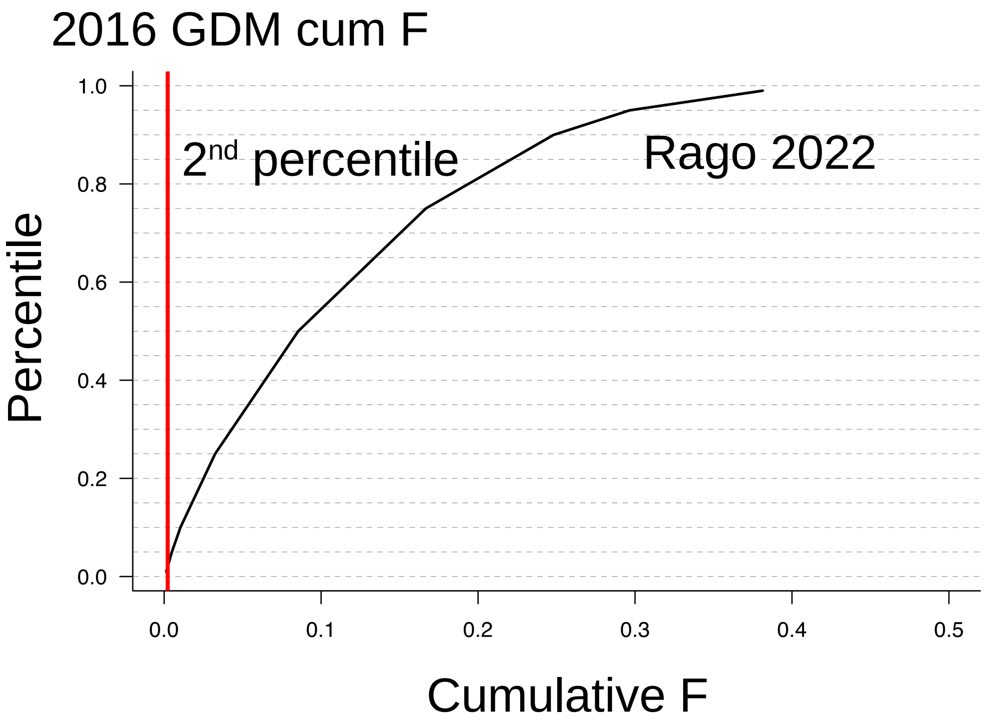
Derived quantities of interest: illill.2016_F2P1E0P1E0.0.apln.apln.pred.BFGS



2016 GDM vs Rago 2022 plausible bounds

Comparison of GDM fishery based estimates (illlill.2016_F2P1E0P1E0.0.apln.apln.pred.BFGS) with Rago 2022 FI survey based estimates





Generalized depletion modeling 2013-2019

"Best" hypotheses & variants. Important issues related to sample size

Catch-ability parameters

Season	Model	Distribution	Method	k.freezer	%_CV	alpha.fr	%_CV	beta.fr	%_CV
2013	0P1P	Negbin	BFGS	4.97E+02	110	1.12	44	0.01	1504
2016	1P1P	Apln	BFGS	5.63E-11	8	1.62	7	1.67	1
2017	1P1P	Normal	BFGS	4.70E-06		0.84	15	1.10	
2018	0P0P	Gamma	BFGS	4.83E-05	4524	0.44	33	1.11	126
2019	1P2P	Normal	BFGS	8.30E-02		0.46	9	0.54	31

Season	Model	Distribution	Method	k.wet	%_CV	alpha.wet	%_CV	beta.wet	%_CV
2013	0P1P	Negbin	BFGS	2.25E-11		0.47	51	2.49	
2016	1P1P	Apln	BFGS	1.52E+00	2	1.34	11	0.29	33
2017	1P1P	Normal	BFGS	4.26E-02	4	0.72	14	0.59	32
2018	0P0P	Gamma	BFGS	1.67E-04	51	1.17	63	0.93	256
2019	1P2P	Normal	BFGS	1.07E-02		0.53	28	0.65	

% CV (SE/Est*100) > %100 or asymptotic SE not produced

Catch perturbations (in-season immigration)

Season	Model	P1.Mag.fr.thou	% CV	Wk.P1.fr
2013	0P1P			
2016	1P1P	90,828	5657	35
2017	1P1P	17,354	3718	24
2018	0P0P			
2019	1P2P	4,361	10363	27

Season	Model	P1.Mag.wet.thou	% CV	Wk.P1.wet	P2.Mag.wet.thou	% CV	Wk.P2.wet
2013	0P1P	287,091	443				
2016	1P1P	37,092,712	22	33			
2017	1P1P	63,596,193	NA	23			
2018	0P0P						
2019	1P2P	66,271,954	684	26	62,144,970	731	31

Fleet specific parameters

Catch-ability & catch perturbations

2019 1P2P model

N weeks = 14

2 ingress events into wet boat fleet

3 catchability params,

2 perturbations (*2 params) = 4

= 7 params

param/data= 7/14 = 0.5

Generalized depletion modeling 2013-2019

Sample sizes

- With weekly time step insufficient

				Weekly step		Daily step	
Season	Weeks	Model	N Params	N_data_wk	Param/Data	N_data_day	Param/Data
2013	14	0P1P	10	28	0.36	98	0.10
2016	19	1P1P	12	38	0.32	133	0.09
2017	16	1P1P	12	32	0.38	133	0.11
2018	12	0P0P	8	24	0.33	84	0.10
2019	14	1P2P	14	28	0.50	98	0.14

Daily time step

- increase precision

- Increase ability to detect in-season migration events including emigration

****Pulses have large influence on quantities of interest***

- Probably need catch rather than landings (0 inflation problem for freezer trawlers)

Generalized depletion modeling

- Could allow risk of overfishing to be assessed while accounting for in-season migration
- Could allow for in-season assessment
- Weekly landings data insufficient & existing weight data not fully representative

Next steps

1) Near term.

Combine data simulation with analysis of existing landings and shorter time step.

a) Can existing landings data with shorter step provide sufficient precision & sensitivity to ingress/egress events? (probably not)

b) Data simulation

Evaluate impacts of sample size, data quality, ingress/egress on parameter sensitivities

c) Develop methods to generate full suite of uncertainty estimates for quantities of interest

2) Medium term

Based on findings of #1) develop collaborative research study/experimental fishery to...

a) develop in-season data & information streams to support GDM

Include in-season information sharing between fishery, assessors and fisheries oceanographers to get inferences about migration right

b) pilot study: evaluate utility of approach in operational assessment