

Yellowfin tuna Spatial assessment modelling workshop

Stock Synthesis (SS)

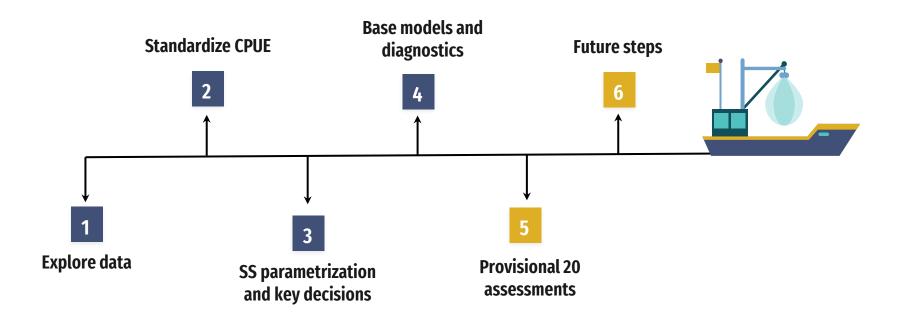
Francisco Izquierdo, Marta Cousido, Giancarlo M. Correa, Maria Grazia Pennino, Santiago Cerviño



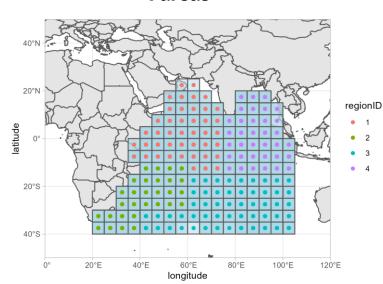




>>> IEO Team modeling approach

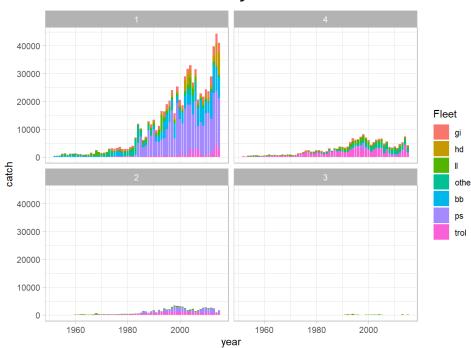


4 areas



1 and 4 spatial areas

Catch by fleet

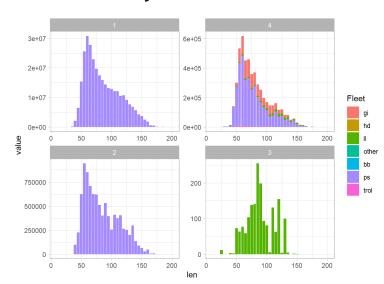


Catch by area: 1>4>2>3

Catch by fleet: ps>trol>bb>other>ll>gi>hd



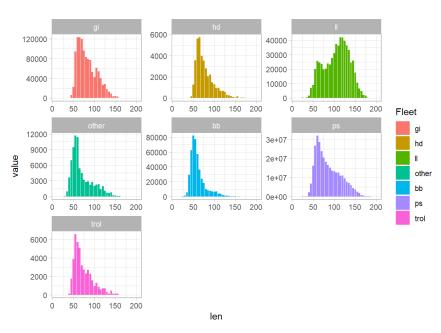
LFD's by area (no scaled)



LFD by area: 1>4>2>3

LFD by fleet: ps>qi>ll>bb>trol>hd>other

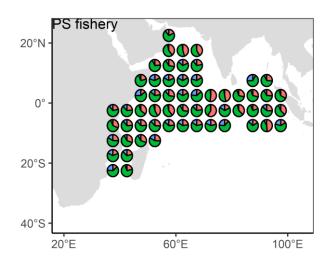
LFD's by fleet (no scaled)



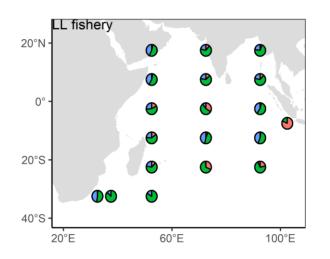
Sizes range around 50 – 150 for all fleets LL catching bigger fish



Fish size by fleet



Smaller individuals targeted by PS (the one used to define recruitment)



Bigger individuals targeted by longline distributed in mainly in área 1, 2, & 4



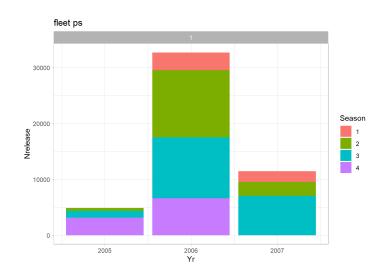
Size range

(0,60]

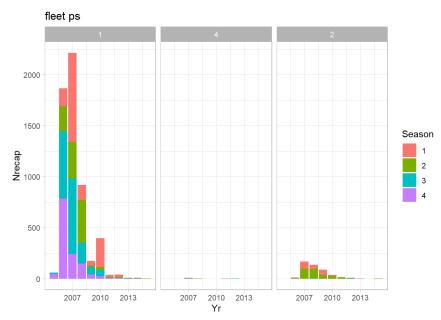
(60, 120]

(120,200]

Tagging data



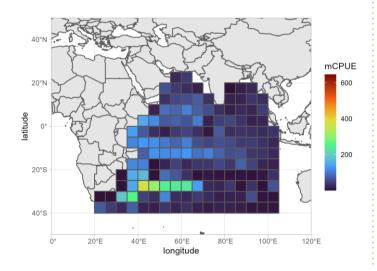
All tag releases made in A1



Recaptures by PS in A1>A2>A4 None in area 3



"The **provided CPUE** is calculated as the number of fish caught by the longline fishery divided by the number of hooks in each cell (as such units for each CPUE index are in N/hooks)"



We fit a Bayesian spatio-temporal models for lattice data with R-INLA.

Continuous response variable: non standardized CPUE (no 0's).

We model the relative abundance CPUE, Zst.

$$Z_{st} \sim Gamma (\mu_{st}, \phi)$$

1) iid:
$$\log(\mu_{st}) = \alpha + a_s + g(t)$$
; $a_s \sim N(0, \sigma_a^2) \& g RW2$

2) besag:
$$\log(\mu_{st}) = \alpha + U_s + g(t)$$
; $U_s \sim N(0,\Sigma) \& g RW2$

3) besag st:
$$\log(\mu_{st}) = \alpha + \bigcup_{st} + g(t)$$
; $U_{st} = W_{st} + \rho U_{st-1}$,

$$W_{st} \sim N(0, \Sigma) \& g RW2$$

R Scripts on **Github**:

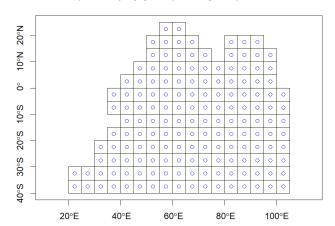
https://github.com/FranIzquierdo/YFT-lattice-st-CPUE-models



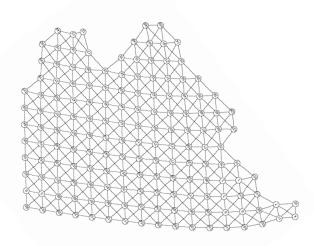
2) Besag spatial effect implies that nearby things are similar

We construct the neighbor **matrix** by polygon contiguity in order to create the spatial (matrix correlation) structure: $xi-xj \sim N$ (0, sigma2) if i and j are neighbours

pts and poly grids (5x5 degrees) WGS84



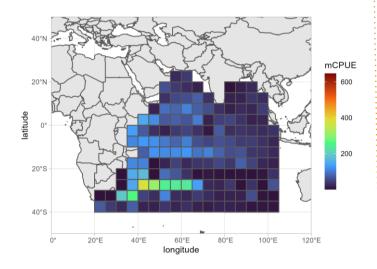
Dimensions: 160 x 160



Besag spatial and spatio-temporal models **SPDE book**: https://becarioprecario.bitbucket.io/inla-gitbook/ch-spatial.html#sec:lattice



"The unstandardized CPUE is calculated as the number of fish caught by the longline fishery divided by the number of hooks in each cell (as such units for each CPUE index are in N/hooks)"



We fit **INLA** spatio-temporal models for lattice data.

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2) besag:
$$\log(\mu_{st}) = \alpha + U_s + g(t)$$
; $U_s \sim N(0,\Sigma) \& g RW2$

3) besag st:
$$\log(\mu_{st}) = \alpha + \frac{U_{st}}{U_{st}} + g(t)$$
; $U_{st} = W_{st} + \rho U_{st-1}$,

$$W_{st} \sim N(0, \Sigma) \& g RW2$$

R Scripts on **Github**:

https://github.com/FranIzquierdo/YFT-lattice-st-CPUE-models





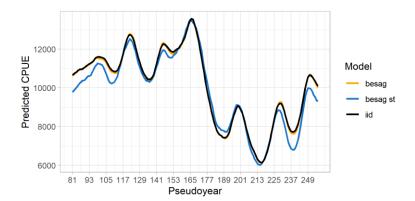
Model selection

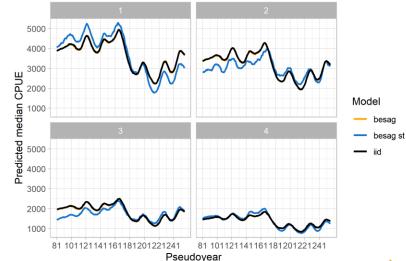
model	dic	waic	Icpo	time
iid	70283.08	70301.38	3.20	203.63
besag	70294.30	70328.79	3.20	181.10
besag st	68204.39	68142.56	3.11	8276.21

The **best model** in terms of godness of fit is the **besag** spatio-temporal model

Predicted CPUE: sum of predicted values in the cells by area in each pseudoyear (scaled indices)

Uncertainty of the model obtained by taking 100 random samples of the posterior distributions (not displayed here)

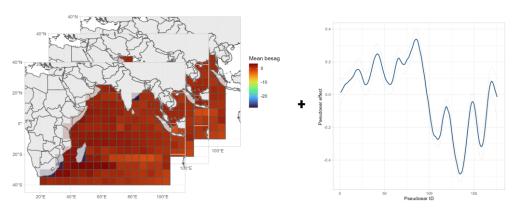






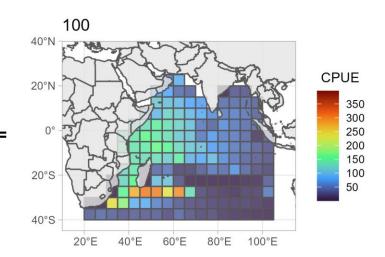
Besag spatio-temporal model: the progressive **spatio-temporal structure** catches the spatial correlation among neighbour polygons along the time

- The spatial polygons evolve differently along time
- Not all time steps have the same spatial distribution

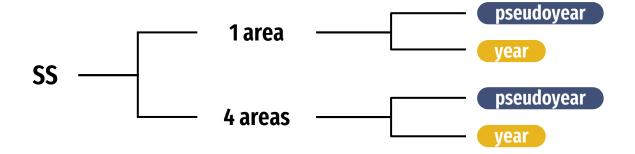


Mean besag spatial effect by year (AR1 time correlation)

Time smoothed (RW2) trend



>>>> 3. SS parametrization and key decisions



- Build a fine scale model configuration with all provided data (0 to 28+ pseudoyears, k seasonal dev., M each quarter)
- Build a model with parameter inputs that we would have in a real case situation (0 to 7+ years, k base, M at age)



>>> 3.1. Parametrization

pseudoyear

Input parameters as provided in the experiment

Age (pseudo-year)	Age (year)	\mathbf{M}	L	Mat	k
1	0.25	0.3358	22	0	0.5
2	0.5	0.2955	35.2865	0	0.75
3	0.75	0.2552	41.384	0	1
4	1	0.2149	45.7348	0	1
5	1.25	0.1746	49.904	0.1	1
6	1.5	0.1343	53.8991	0.15	1.8
7	1.75	0.1343	57.7273	0.2	1.8
8	2	0.1343	64.2198	0.3	1.2
9	2.25	0.1343	74.721	0.5	1.2
10	2.5	0.1343	85.5489	0.7	1

Biology

- Natural mortality (M): summed across seasons for each age
- Maturity: values averaged across seasons
- **K Von Bert.:** k base = 0.45

	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7
М	1.23	0.66	0.54	0.73	0.76	0.56	0.54	0.54
Mat.	0	0.12	0.6	1	1	1	1	1



pseudovear and year

Spawner-Recruitment

LN(R0)	BH steep	sigmaR	SR regime	SR autocorr
0.68	0.8	0.6	0	0

We fixed all parameters unless R0

Growth

 L_{inf} 145 cm Lmin 22 cm k (base) 0.455

Length of weight: a $2.459e^{-5}$

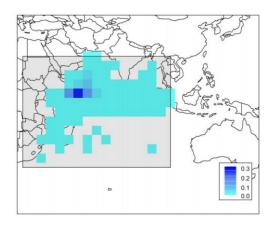
Length of weight: b 2.9667 All parameters were set fixed as provided by the experiment

CV_Young and CV_old set to 0.1

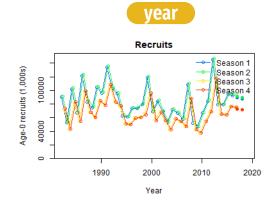
>>> 3.2. Key decisions

pseudoyear

 1A y 4A, recruitment into the population established in each pseudoyear.



Recruitment



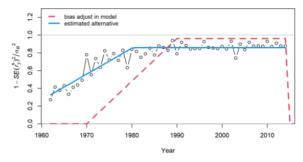
- 1A recruitment settlements in months1, 4, 7 & 10
- 4A recruitment settlements in area 1, months 1 & 7 (time-varying effect)



Recruitment deviations

pseudovear and vear

- We run the model with hessian in order to get the recruitment deviation suggested from SS
- Run the model again with these values
- Afterthat, we changed the last early year no bias adjustment from 1950 to 1970 (same in pseudoyears) for being the period which started to have good information about LFDs



Points are transformed variances. Red line shows current settings for bias adjustment (which may or may not be an improvement. For more information, see

Methot, R.D. and Taylor, I.G., 2011. Adjusting for bias due to variability of estimates

Estimated alternative inputs to SS control file associated with blue line in figure:

```
# last early yr nobias adj in MPD
 # first vr fullbias adi in MPD
# last vr fullbias adi in MPD
# first recent yr nobias adj in MPD
# max bias adi in MPD (1.0 to mimic pre-2009 models)
```

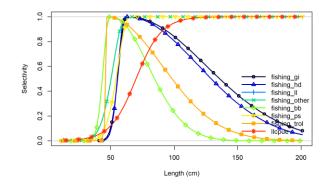


3.2. Key decisions

Fleet's selectivity

pseudoyear and year

- We tried selex at age & selex at length configurations for year and pseudoyear models
- Hypothesis: selex at age may work better in the pseudoyear model because there is not a big difference in growth across pseudo-ages
- Finally, selex at age was selected for pseudoyear and selex at length was the best option for year



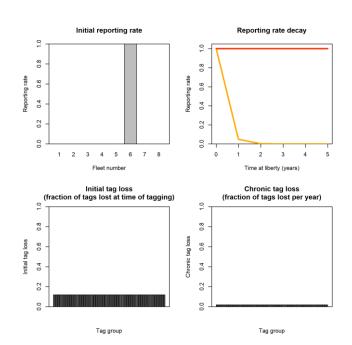
- 1A, set all fleets DN unless LL
- **4A,** set all fleets DN unless LL.

As a first approach, we mirrored selectivity parameters of the same fleets across areas



>>>> 3.2 Key decisions

Tagging data



pseudoyear and year

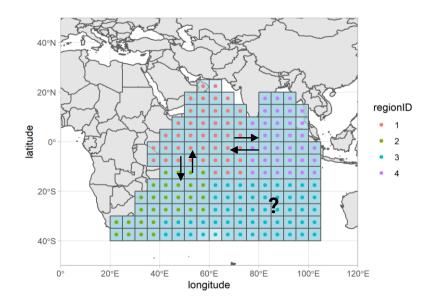
For **1A** and **4A**, we **auto-generated** tag parameters

Some information taken from **report** references:

- Reporting rate only for PS
- Initial tag loss fixed around 10%
- Tag chronic loss fixed around 3%
- Mixing latency period = 3 (values explored)

3.2 Key decisions

Movement



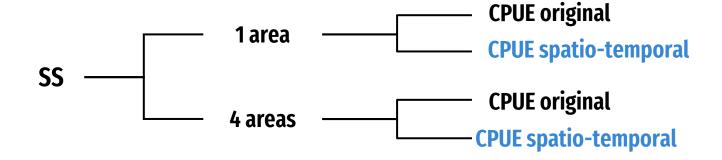
Information from taging: A1 \rightarrow A1, A1 \rightarrow A2, A1 \rightarrow A4

What about A3?

- CPUE st maps indicate area 3 and 4 are similar
- The CPUE st is scaling the relative abundance by area, so we assumed that the 4 areas have constant catchability (Q)
- We think big individuals must come back to A1 for reproduction

We defined the **movements** between areas: $A1 \rightarrow A1$, $A2 \rightarrow A2$, $A3 \rightarrow A3$, $A4 \rightarrow A4$, $A1 \rightarrow A2$, $A2 \rightarrow A1$, $A1 \rightarrow A4$, $A4 \rightarrow A1$, $A3 \rightarrow A4$, $A4 \rightarrow A3$

4. Base models and diagnostics



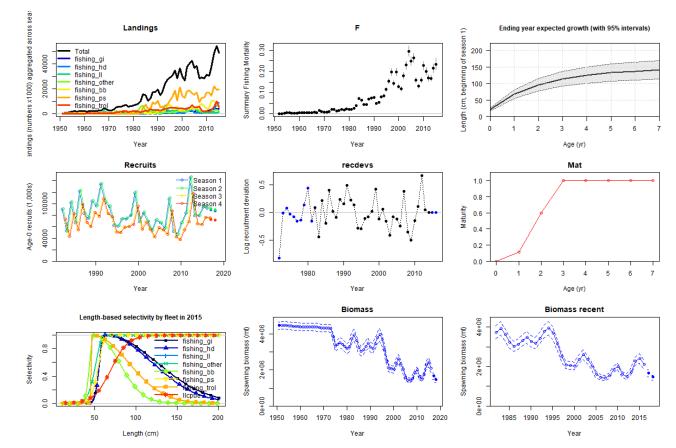
Both CPUEs showed a good performance across the different configurations

We decided to **select CPUE spatio-temporal** models because they take into account the spatio-temporal autocorrelation



→ 4.1 Base model 1 area





Settings:

- CPUE besag st
- Tagging data (Latency period bias)
- 4 settlements
- LFD ESS 25
- PS, LL & OTHER estimated as logistic

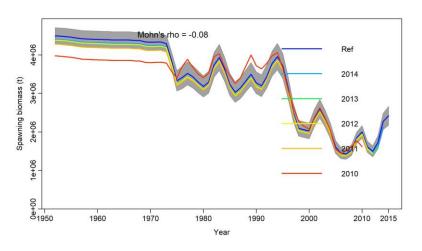




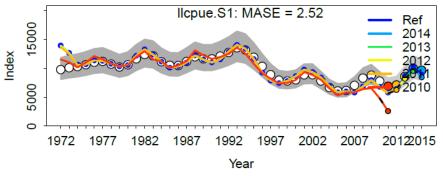
→ 4.1 Base model 1 area



Retros and diags



Retrospective pattern of SSB seems fine unless the retro-5



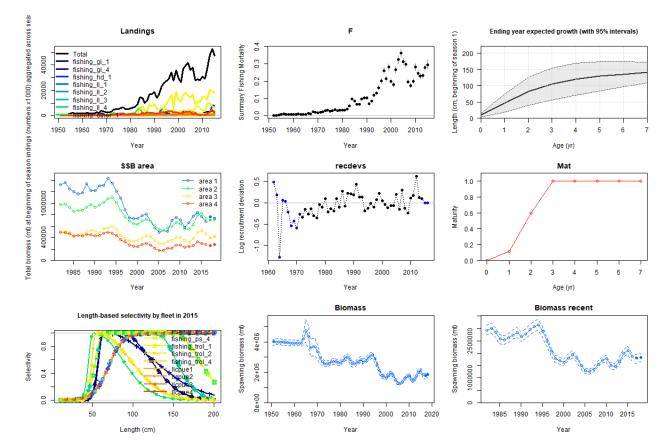
Retrospective pattern of index seems correct unless the retro-5





4. 2 Base model 4 areas





Settings:

- CPUE besag st
- Shared Q
- LFD ESS 25
- Settlements 1,7 in A1
- Movement defs
- Tagging data

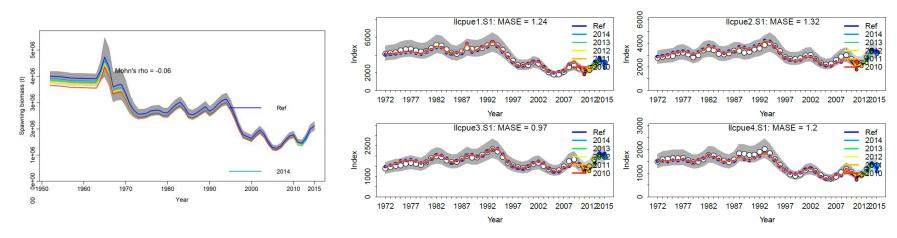




4. 2 Base model 4 areas



Retros and diags

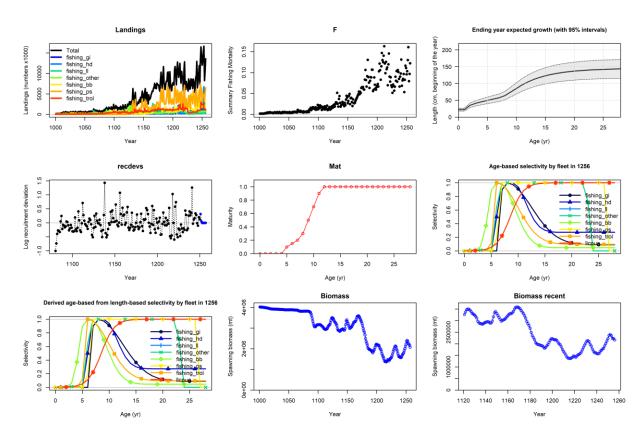


Retrospective pattern of SSB and index seems correct



→ 4.3 Base model 1 area

pseudoyear



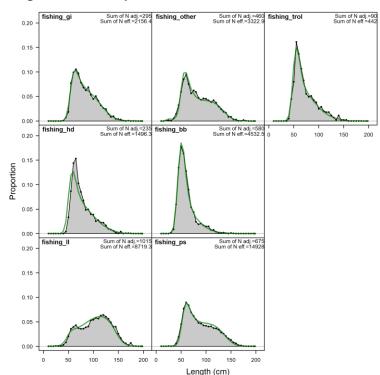
Includes:

- CPUE besag st
- Tagging data
- LFD ESS 25
- PS, LL & OTHER estimated as logistic

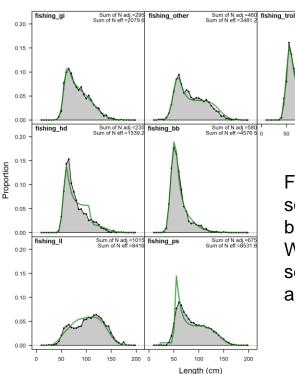
→ 4.3 Base model 1 area

pseudoyear

Age-selectivity:



Length-selectivity:



Francis (2016): "In most cases, selectivity should be lengthbased"

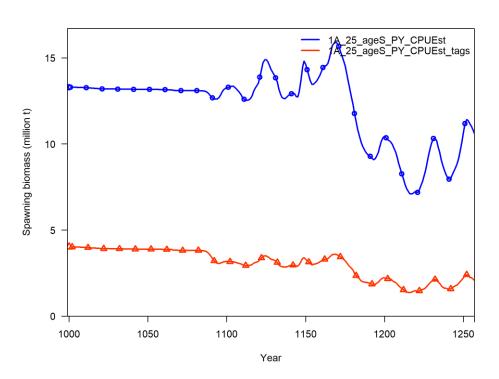
Sum of N adj.=90 Sum of N eff.=454.7

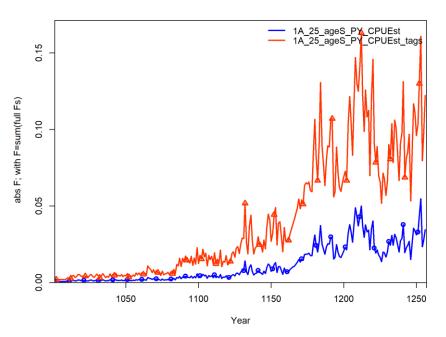
50 100 150

Why smaller residuals of ageselectivity?: effects of length-atage variability?

>>> 4.3 Base model 1 area

pseudoyear





What information provides tagging data in a 1A model?

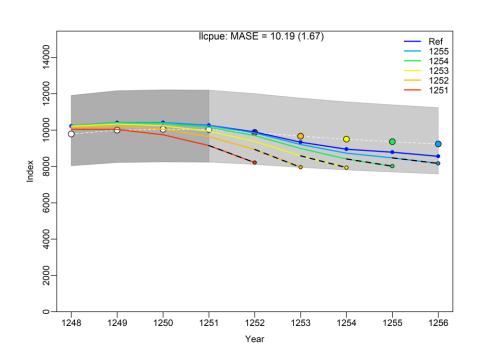


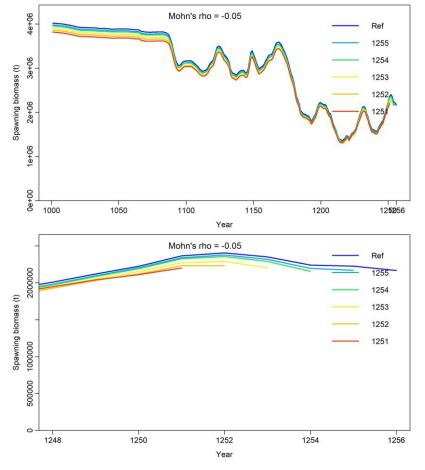


→ 4.3 Base model 1 area

pseudoyear

Retros:





Retrospective SSB pattern looks fine.



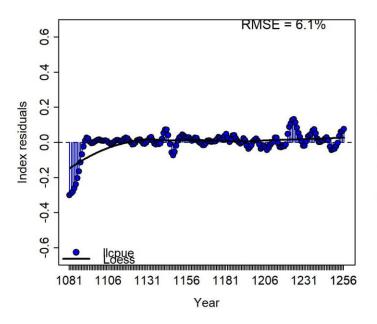




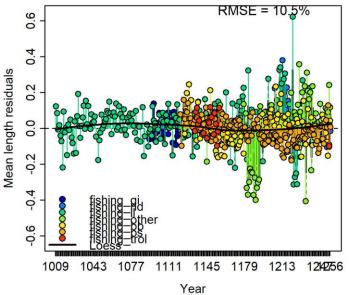
★ 4.3 Base model 1 area

pseudoyear

Diagnostics:



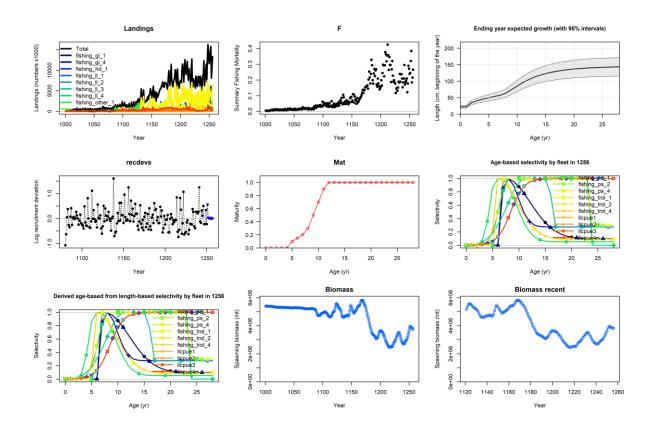
CPUE: Negative residuals for early years. Mean length: Some fisheries did not pass test.





4. 4 Base model 4 areas

pseudoyear



Includes:

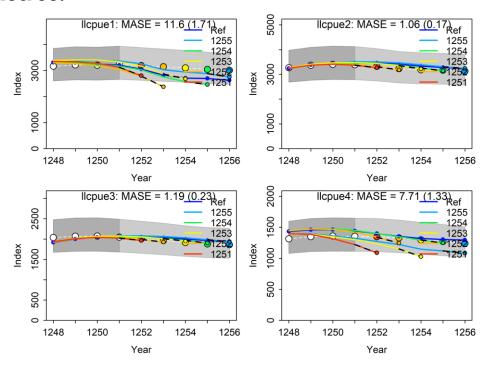
- CPUE besag st
- Shared Q
- LFD ESS 25
- Tagging data

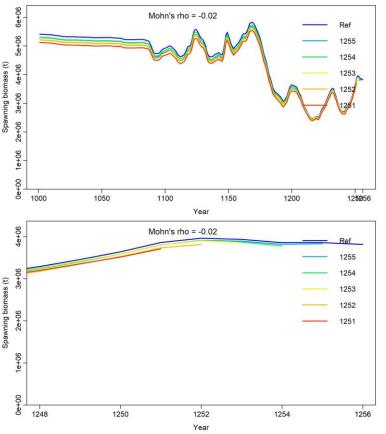


> 4. 4 Base model 4 areas

pseudoyear

Retros:







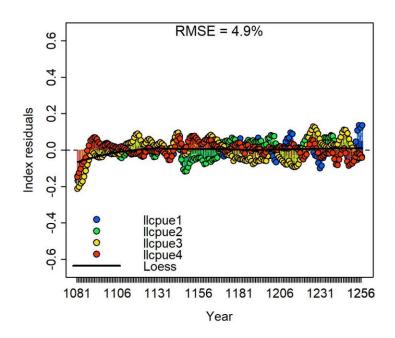




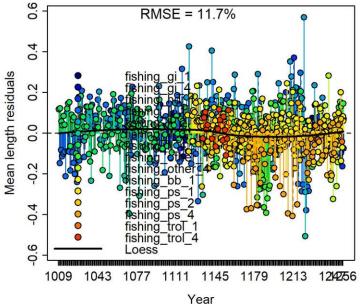
★ 4.3 Base model 4 area

pseudoyear

Diagnostics:



CPUE: Negative residuals for early years. Mean length: Some fisheries did not pass test.





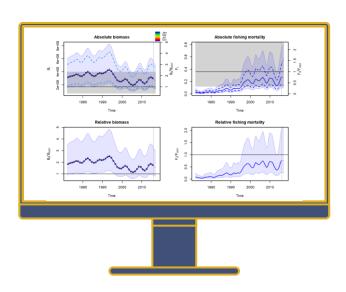
Cross-check: Surplus Production model

Data-moderate model: A stochastic surplus production model in continuous time (**SPiCT**; Pedersen and Berg, 2017)

Input data: catch data in tonnes (transformation catch numbers using length frequency distributions)

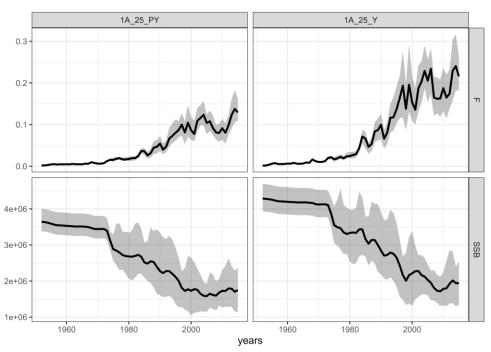
Different trials for annual data:

- a) catch and original CPUE
- b) catch and spatio-temporal CPUE



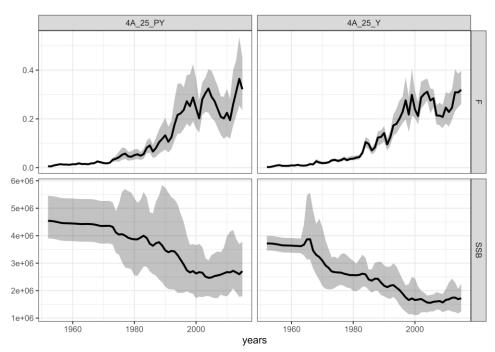
Convergence problems using catch from 1954 → Start catch time series at 1972 (first year of CPUE).

5.1 Provisional 20 assessments 1A



	year	pseudoyear
% Convergents	0.85	0.95
Catch RMSE mean	0	0
Catch MAPE mean	0	0
Catch RMSE sd	0	0
Catch MAPE sd	0	0
CV SSB mean	12.37	13.6
Cv F mean	15.89	13.6
CV rec mean	20.04	23.6
CV ssb sd	5.74	6.6
Cv F sd	5.05	5.1
Cv rec sd	11.05	15

5.2 Provisional 20 assessments 4A

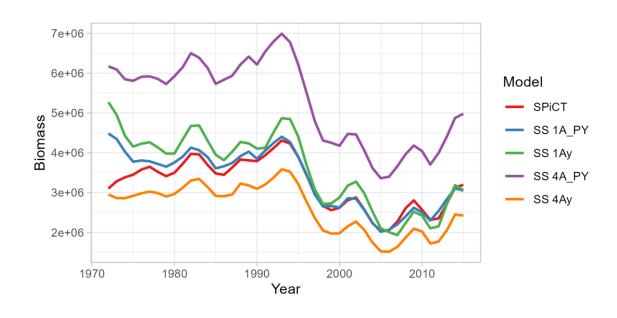


	year	pseudoyear
% Convergents	0.75	0.9
Catch RMSE mean	0	0
Catch MAPE mean	0	0
Catch RMSE sd	0	0
Catch MAPE sd	0	0
CV SSB mean	12.72	19.4
Cv F mean	12.29	22.1
CV rec mean	17.53	32.5
CV ssb sd	5.19	5.6
Cv F sd	4.62	4.8
Cv rec sd	9.68	17.4



→ 4.5. SPiCT model

Cross-check: Surplus Production model

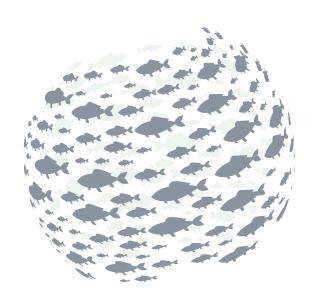


Diagnostic

- SPiCT estimates have same trends as 1A and 4A models for both configurations
- SS 4A_PY for a single replicate*

6. Future steps

- Keep exploring trials without tagging data
- Try different recruitment settlement settings in 4A models
- Explore different movement settings in 4A
- Compare and discuss pseudoyear and year differences (i.e., recruitment settlements)
- Compare and discuss 1A and 4A configurations



THANKS!





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https://github.com/FranIzquierdo/NOAA-YFT-workshop-IEO-team https://github.com/gmoroncorrea/SpatialStockAssessment_SpanishGroup