NPFC-2023-SC08-IP10

1. CPUE standardization
2. Stock assessment
3. Abundance projection

# of NFS in the Northwest Pacific Ocean based on Chinese jigging fisheries data

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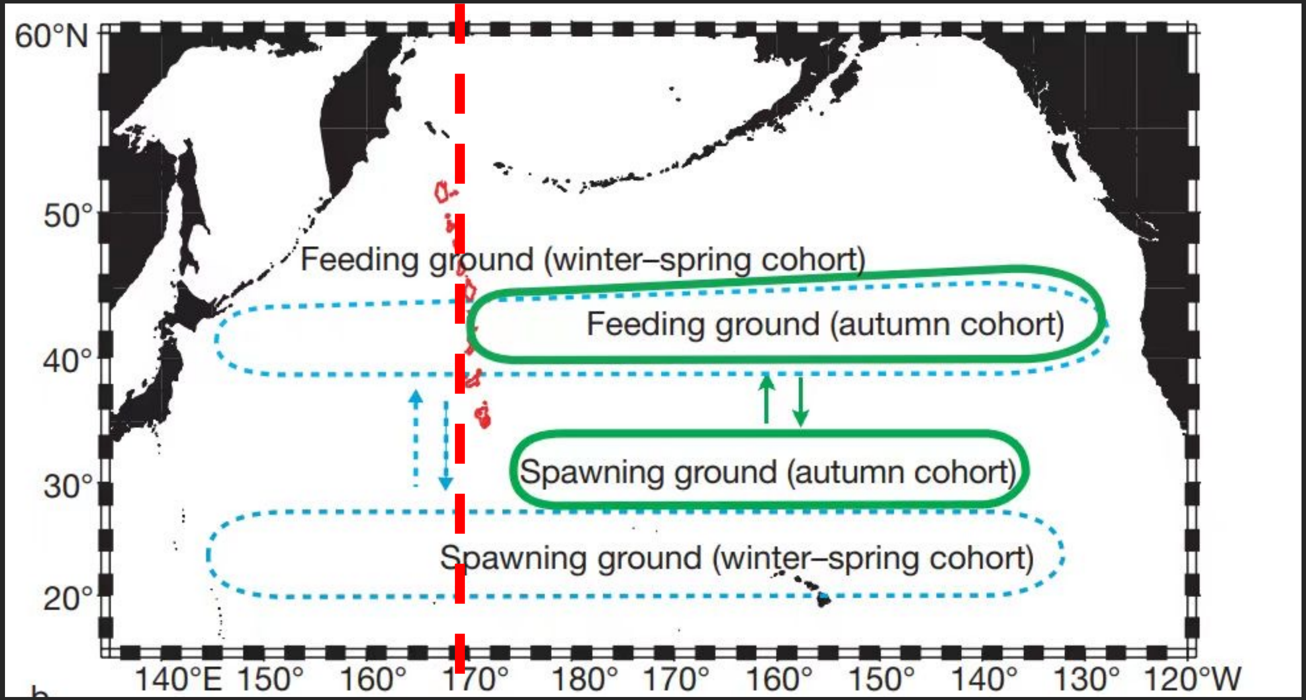
Background



Winter-spring cohort
(East cohort)

Autumn cohort
(West cohort)

May – November

May – August

(Ichii et al. 2011; Han et al., 2022)

Fig. 1 Spatial structures for NFS in the Northwest Pacific Ocean

Fisheries data

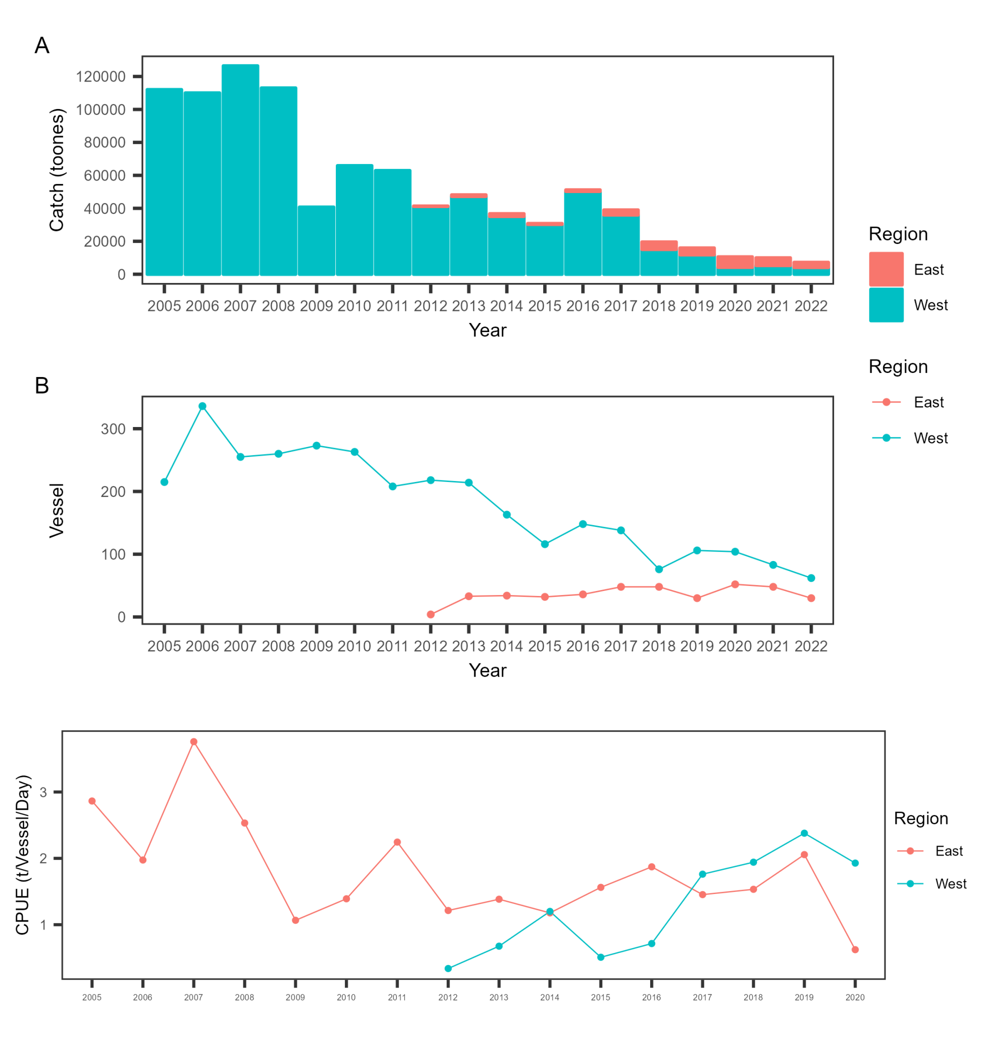


Fig. 2 Chinese catch, vessel, and nominal CPUE during 2005 – 2020

Fisheries data

0.5 × 0.5 grid

Monthly

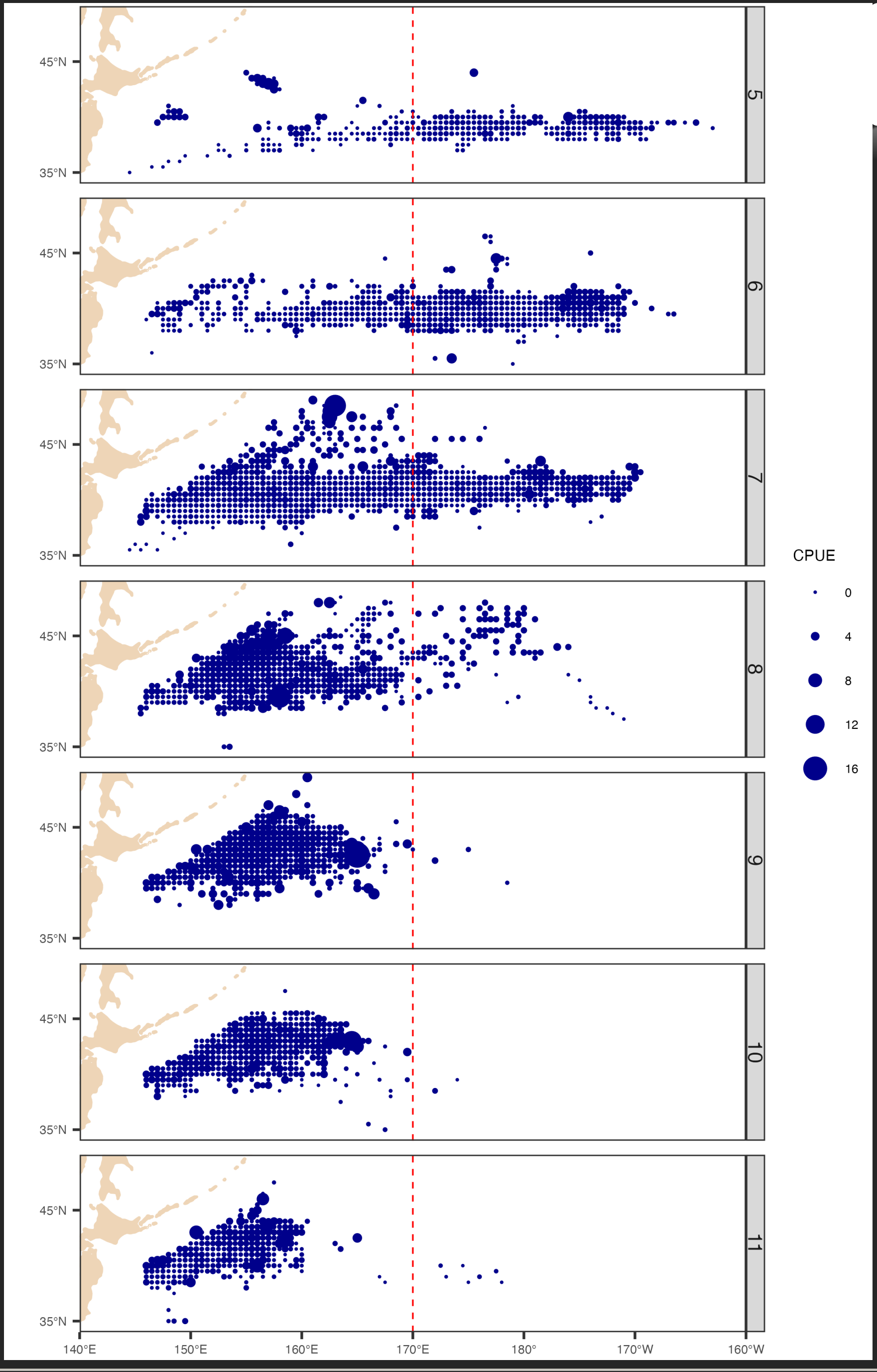


Fig. 3 Spatial distribution of mean nominal CPUE for the autumn cohort and the winter-spring cohort of NFS by Chinese squid jigging fisheries.

Environmental data

- Water temperature, Water salinity, Chlorophyll, Dissolved Oxygen at 31 layers (0.5, 1 .5, 2.6, 3.8, 5.1, 6.5, 8.0, 9.8, 11.7, 13.9, 16.5, 19.4, 22.7, 26.5, 30.8, 35.7, 41.1, 47.2, 53.8, 61.1, 69.0, 77.6, 86.9, 97.0, 108.0, 120.0, 133.0, 147.4, 163.1, 180.5, 199.7), SSH, MLD, DT0_30, from Copernicus Marine Data Store, Nino34_A from NOAA

- Monthly environmental data converted at 0.5 × 0.5 spatial resolution to match fisheries data

- 129 potential explanatory variables and 1 dependent variable

(Wang et al., 2015, 2016, 2020, 2022, 2023

Yu et al., 2015, 2016, 2017, 2019, 2020, 2021, 2022, 2023)

1. CPUE standardization

Methods

- Generalized additive model (GAM)
- Random forest (RF) model
- Extreme Gradient Boosting Decision Tree (XGB) model

Methods

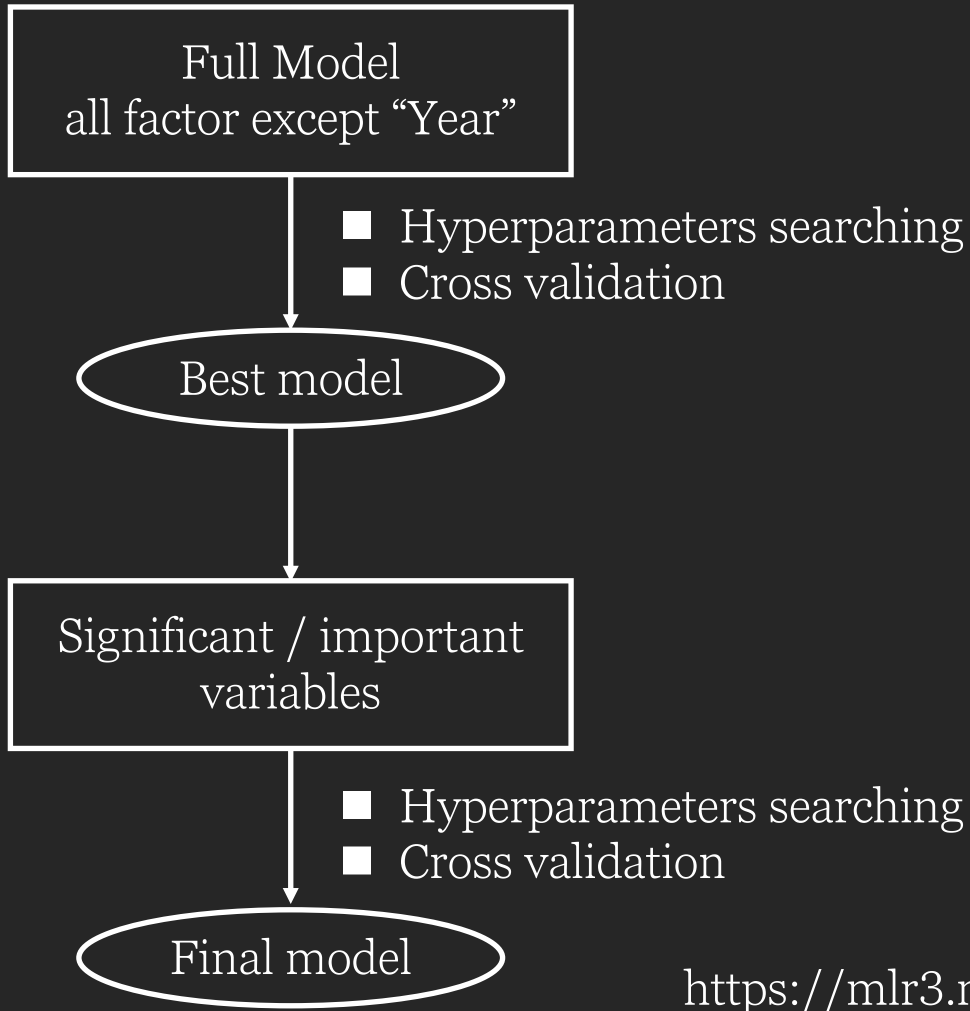
- GAM

```
modGAM2  = gam(CPUE+0.1 ~
                 s(Month, k=4, bs='tp') +
                 te(Lon, Lat, bs=c("tp", "tp"), k=c(5, 5))+
                 s(Temp_0.5, bs="tp")+
                 s(Temp_30.8, bs="tp")+
                 s(Temp_97.0, bs="tp")+
                 s(DT0_30, bs="tp")+
                 s(Sali_0.5, bs='tp')+
                 s(Chl_0.5, bs='tp')+
                 s(SSH, bs='tp')+
                 s(MLD, bs='tp')+
                 s(Nino34_A, bs='tp')+
                 s(Year, k=5, bs="re"),
               knots=list(Month=c(5, 8)),
               data=data,
               method="REML", family = Gamma(link = "log"))
```

(Wang et al., 2022, 2023)

Methods

- RF XGB



https://mlr3.mlr-org.com/

Fig. 4 Flowchart of tuning RF and XGB

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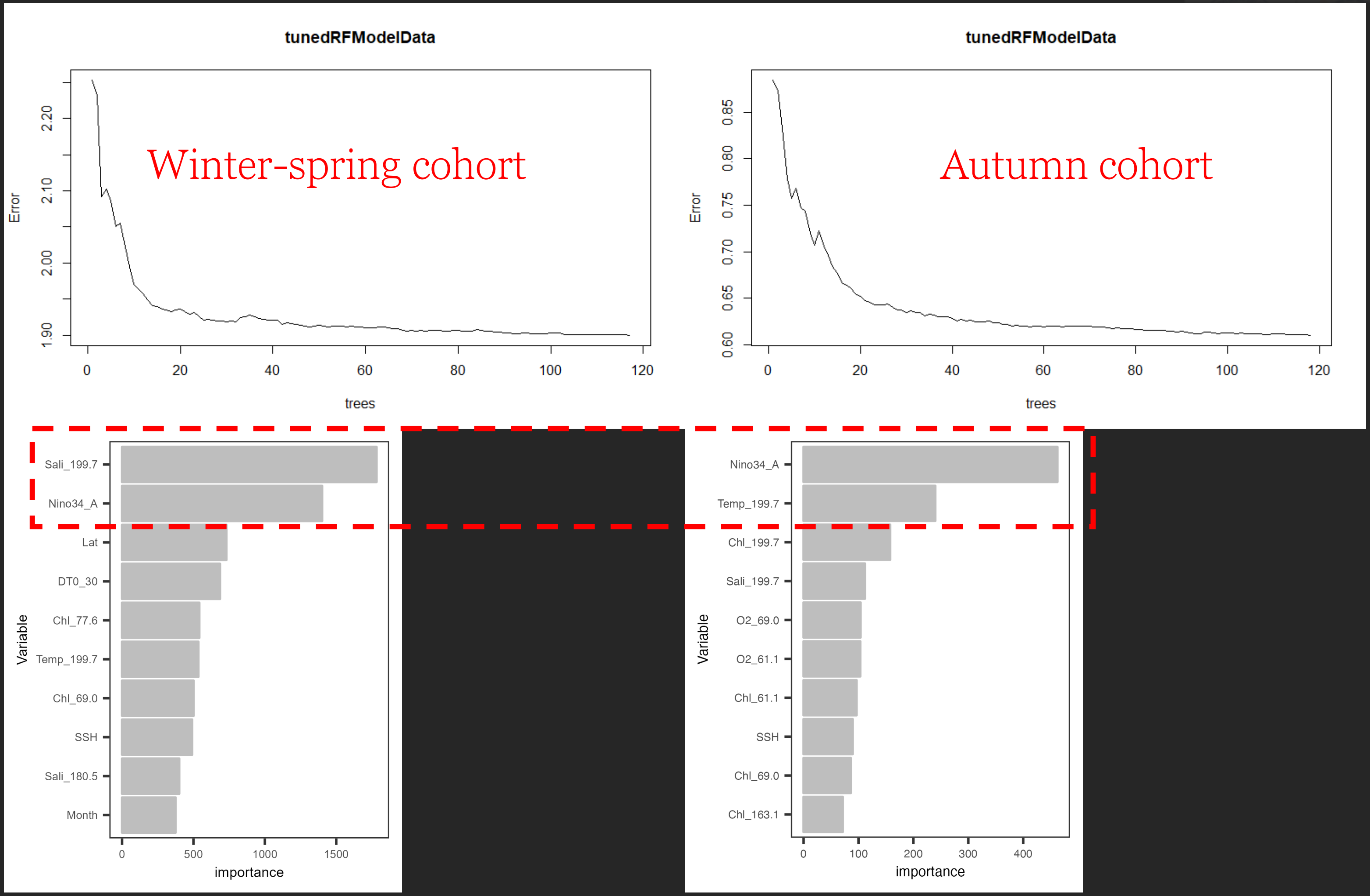
Results---GAM

```
Family: Gamma
Link function: log

Formula:
CPUE + 0.1 ~ s(Month, k = 6, bs = "tp") + te(Lon, Lat, bs = c("tp",
    "tp"), k = c(5, 5)) + s(Temp_0.5, bs = "tp") + s(Temp_97.0,
    bs = "tp") + s(DT0_30, bs = "tp") + s(Chl_0.5, bs = "tp") +
    s(SSH, bs = "tp") + s(MLD, bs = "tp") + s(Nino34_A, bs = "tp") +
    s(Year, k = 5, bs = "re")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.54450    0.01108   49.14   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                   edf Ref.df      F p-value
s(Month)     4.367e+00  4.812 23.909 < 2e-16 ***
te(Lon,Lat)  1.751e+01 19.355  8.537 < 2e-16 ***
s(Temp_0.5)  7.080e+00  8.161  6.860 < 2e-16 ***
s(Temp_97.0) 7.854e+00  8.641 15.324 < 2e-16 ***
s(DT0_30)    4.561e+00  5.701 17.588 < 2e-16 ***
s(Chl_0.5)   6.443e+00  7.628  3.036 0.00377 **
s(SSH)       7.540e+00  8.451 10.446 < 2e-16 ***
s(MLD)       7.718e+00  8.571 10.801 < 2e-16 ***
s(Nino34_A)  7.389e+00  8.362  6.506 < 2e-16 ***
s(Year)      7.690e-06  1.000  0.002 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.134   Deviance explained = 16.7%
-REML =  14286  Scale est. = 0.59663   n = 9717
```

```
Family: Gamma
Link function: log

Formula:
CPUE + 0.1 ~ s(Month, k = 4, bs = "tp") + te(Lon, Lat, bs = c("tp",
    "tp"), k = c(5, 5)) + s(Temp_0.5, bs = "tp") + s(Temp_30.8,
    bs = "tp") + s(Temp_97.0, bs = "tp") + s(DT0_30, bs = "tp") +
    s(Sali_0.5, bs = "tp") + s(Chl_0.5, bs = "tp") + s(SSH, bs = "tp") +
    s(MLD, bs = "tp") + s(Nino34_A, bs = "tp") + s(Year, k = 5,
    bs = "re")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.18154    0.01847   9.828   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                   edf Ref.df      F  p-value
s(Month)     2.697e+00  2.914  3.022  0.01886 *
te(Lon,Lat)  1.098e+01 13.231  4.350  < 2e-16 ***
s(Temp_0.5)  2.890e+00  3.943  2.708  0.04208 *
s(Temp_30.8) 3.721e+00  4.825  2.605  0.02530 *
s(Temp_97.0) 5.210e+00  6.438  6.271 1.17e-06 ***
s(DT0_30)    2.800e+00  3.583  2.427  0.04311 *
s(Sali_0.5)  6.209e+00  7.383  7.741  < 2e-16 ***
s(Chl_0.5)   6.466e+00  7.619  7.287  < 2e-16 ***
s(SSH)       5.616e+00  6.823  3.830  0.00053 ***
s(MLD)       5.740e+00  6.932  4.837 2.49e-05 ***
s(Nino34_A)  7.671e+00  8.511 58.307  < 2e-16 ***
s(Year)      5.067e-06  1.000  0.000  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Rank: 109/110
R-sq.(adj) =  0.284   Deviance explained = 29.7%
-REML =   2497  Scale est. = 0.40654   n = 2383
```

Winter-spring cohort　　　　Autumn cohort

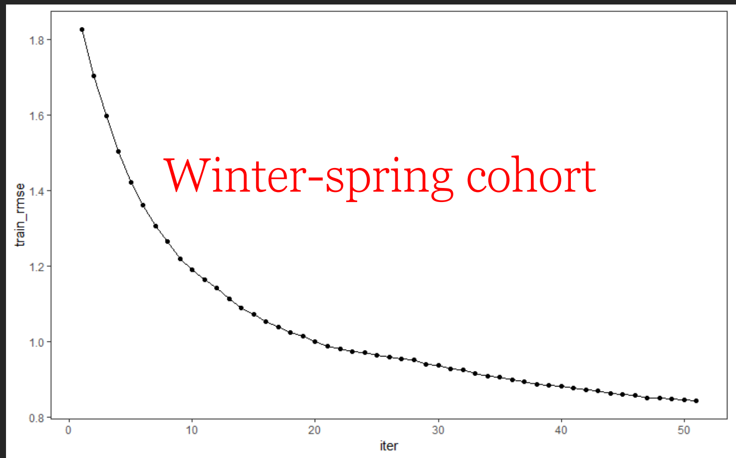
Results --- RF

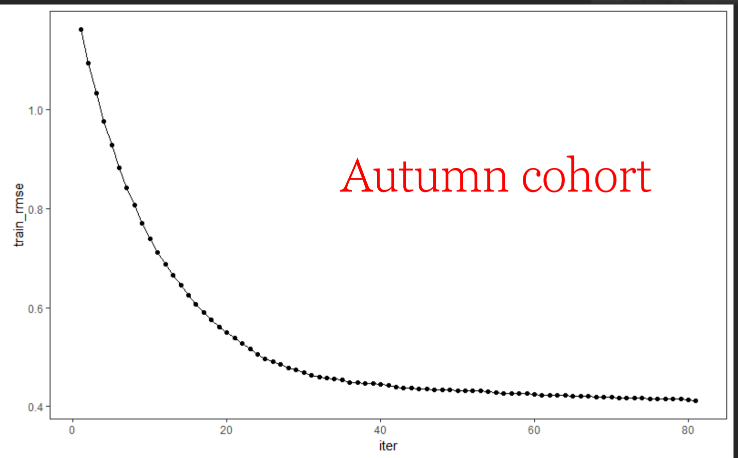


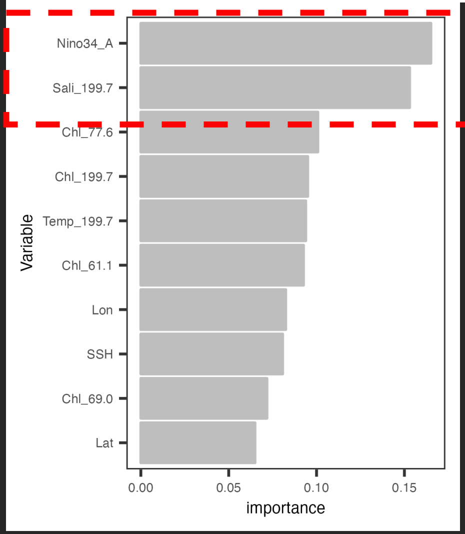

```
> performance(RFPred, measures = list(mse, rsq))
      mse       rsq
1.5981284 0.3376889
```

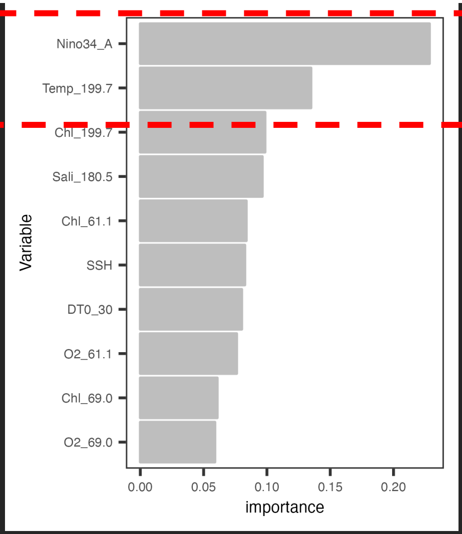
```
> performance(RFPred, measures = list(mse, rsq))
      mse       rsq
0.3691212 0.6355093
```

Result --- XGB









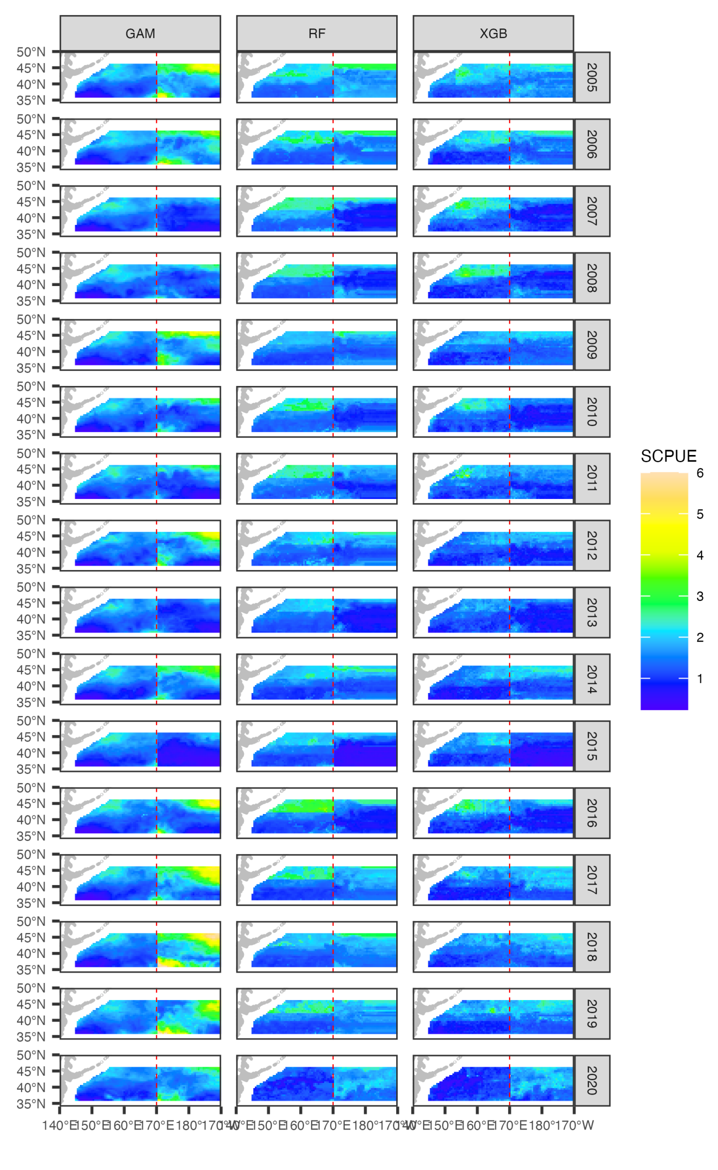

```
> performance(XGBPred, measures = list(mse, rsq))
      mse       rsq
0.7119338 0.7049538
```

```
> performance(XGBPred, measures = list(mse, rsq))
      mse       rsq
0.1703482 0.8317888
```

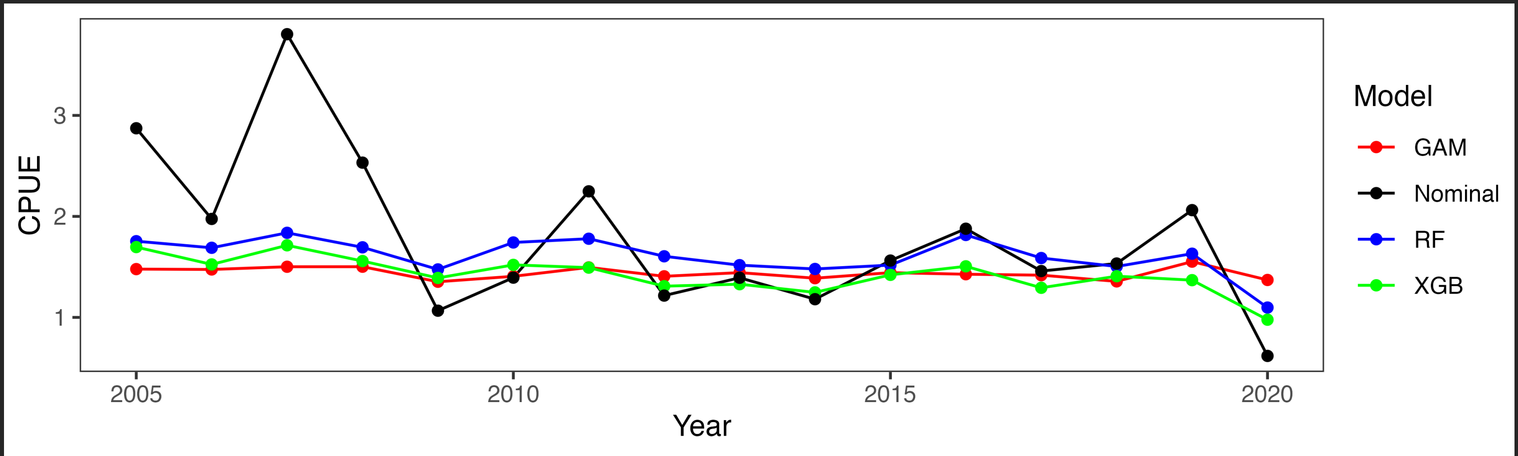
Results --- performance

Model	GAM	RF	XGB
Winter-spring cohort	$R^2 = 0.13$	$R^2 = 0.33$	$R^2 = 0.70$
Autumn cohort	$R^2 = 0.30$	$R^2 = 0.63$	$R^2 = 0.83$

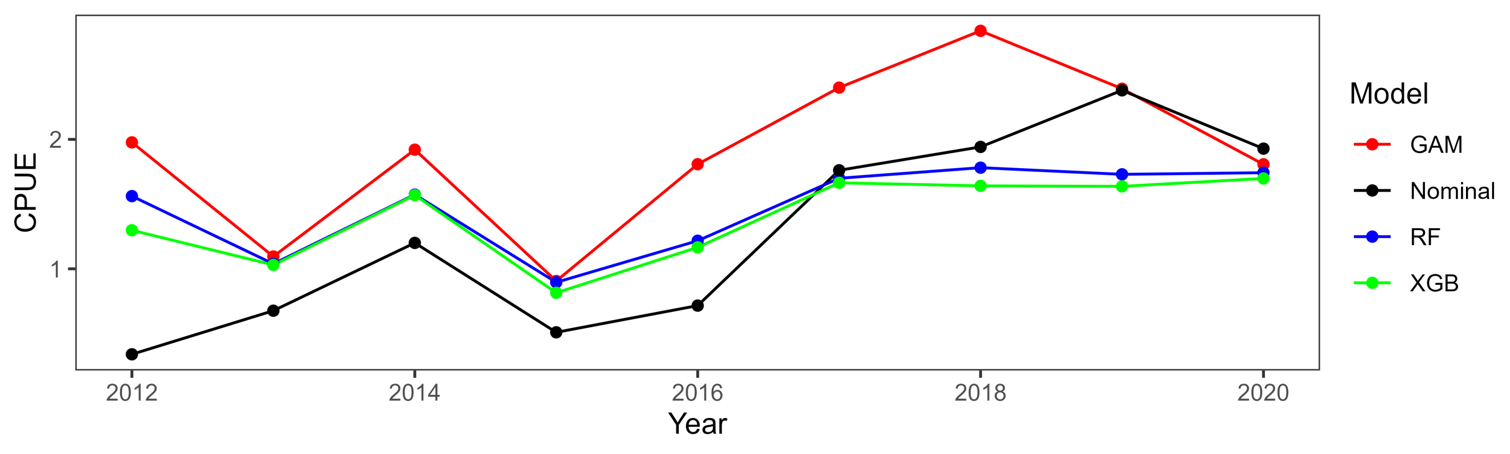
Results -- distribution of predicted CPUE



Results – Abundance index



Standardized CPUE for the winter-sprint cohort



Standardized CPUE for the autumn cohort

2. Stock assessment

Biological feature for squids

1. **Short life spans** → a more data-intensive approach to monitoring, with high population sampling frequency over short time periods

2. **Time-consuming ageing techniques** → age-based models impractical

3. **Extensive ontogenetic migrations** → using "closed population" assumption with caution

4. **Complex population structure** → Time series analyses that extrapolate cohort numbers from population size structures should therefore not usually be used

5. **Rapid growth rates** → models are inappropriate if they use von Bertalanffy parameters or do not account for a semelparous life history

(Arkhipkin et al., 2005, 2008, 2020; Keyl et al., 2008; Rosa et al., 2013)

Alternative SA methods for squid

Table 1. Examples of cephalopod stock assessment methods

Method	Time step	Data type	Data requirements	RPs
Index based	Year (by cohort)	Poor	Fishery independent Mean body weight Fishery catch/survey biomass	B_{Lim}, B_{MSY}, $F_{50\%}$
Swept-area	Synoptic (by cohort)	Poor	Fishery independent Trawl position, swept-area Optionally age, length, sex	B_{MSY} proxy
Catch-only	Year	Poor	Fishery catch	B_{MSY}, F_{MSY}
Eggs- and yield-per-recruit models	Week	Rich	Spawning age Natural mortality-at-age Mean weights-at-age Fishery selectivity-at-age	$F_{50\%}$, $F_{40\%}$, $F_{0.1}$, F_{Max}
Production models	Year	Rich	Fishery catch Abundance index	B_{MSY}, F_{MSY}
Cohort models	Month	Rich	Length/age distributions Fishery CPUE Catch length–frequency	B_{Lim}, %MSP
Two-stage models	Year	Rich	Fishery catch Abundance index Catch length–frequency	E_{Max}, $E_{40\%}$, %MSP
Empirical forecasting	Year	Poor	Environmental indices Recruitment index	B_{Lim}
Depletion models	• Day • Week • Month	Rich	Fishery CPUE Individual weight Maturity	%MSP

These biological characteristics make it difficult to use complex models

(Arkhipkin et al., 2005, 2008, 2020)

JABBA Model prior setting

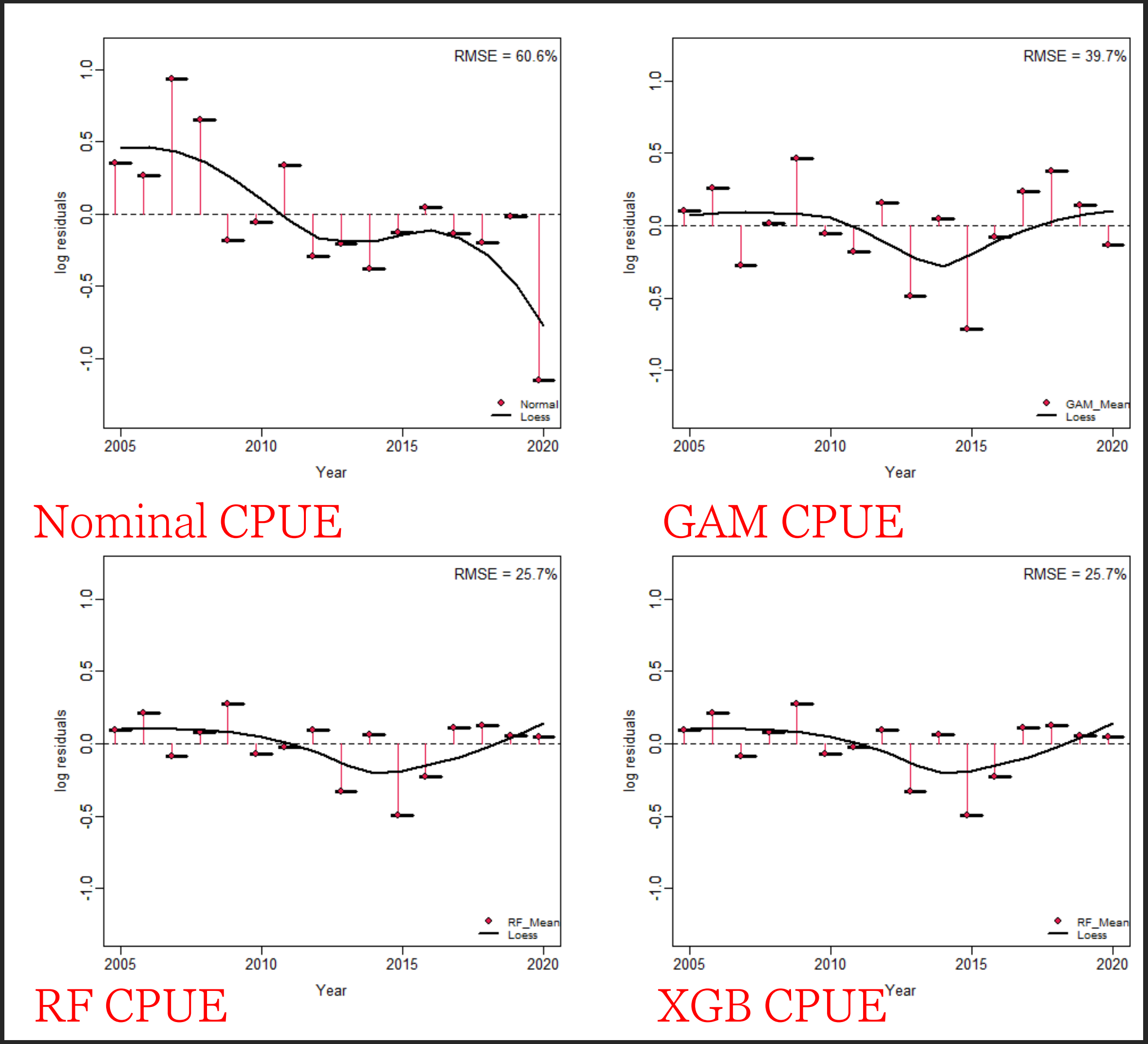
	q Catchability coefficient	K Carrying capacity	r Intrinsic rate of growth
Uniform distribution	$U(1\times10^{-6},3\times10^{-5})$	U(10,100)	U(0.6,1.5)

- m=2， Scheafer function

$$SP=\frac{r}{m-1}B\left[1-\left(\frac{B}{K}\right)^{m-1}\right]$$

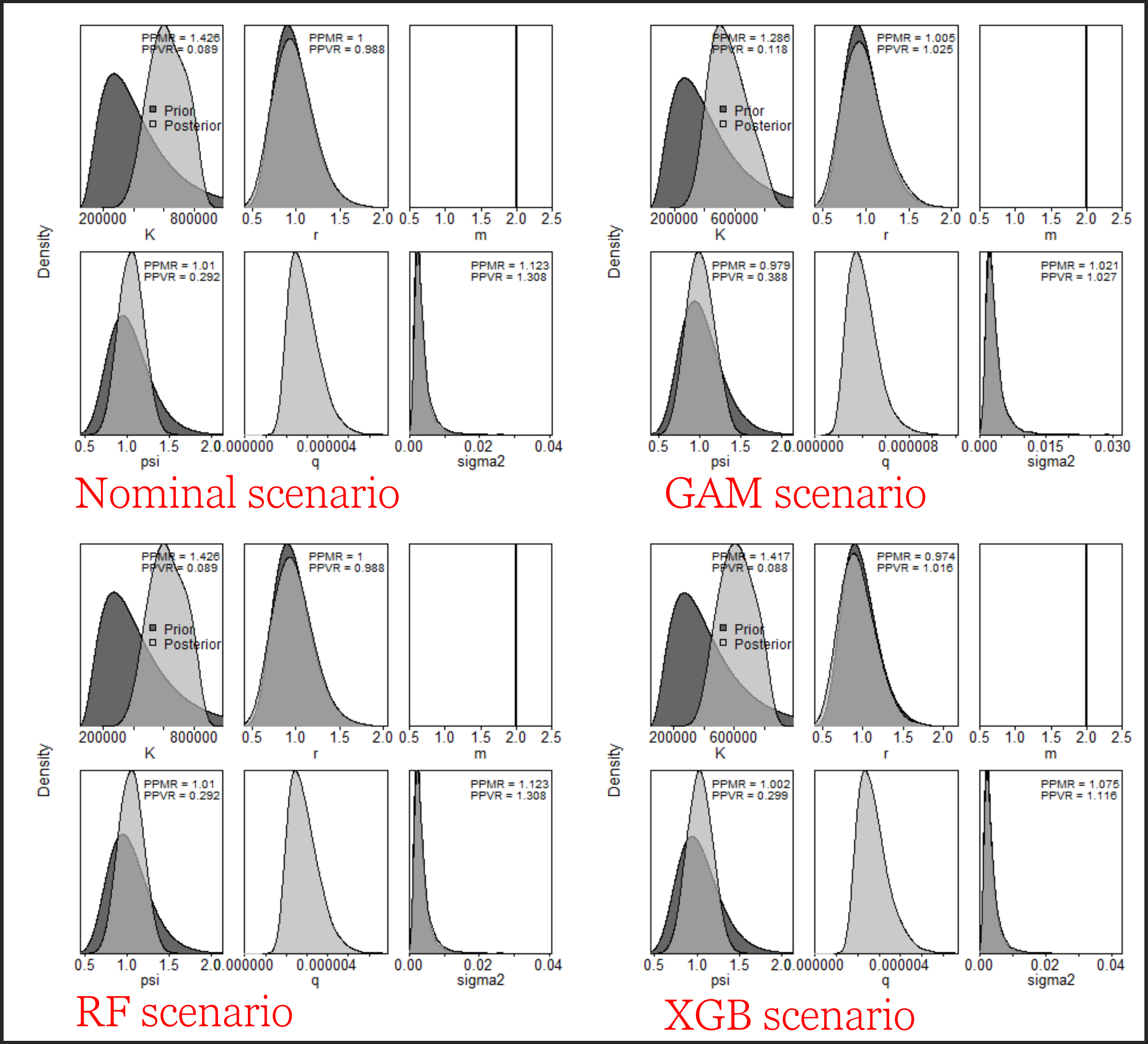
(Chen et al., 2011; Wang et al, 2017, 2018; FishBase)

JABBA model diagnostics for winter-sprint cohort

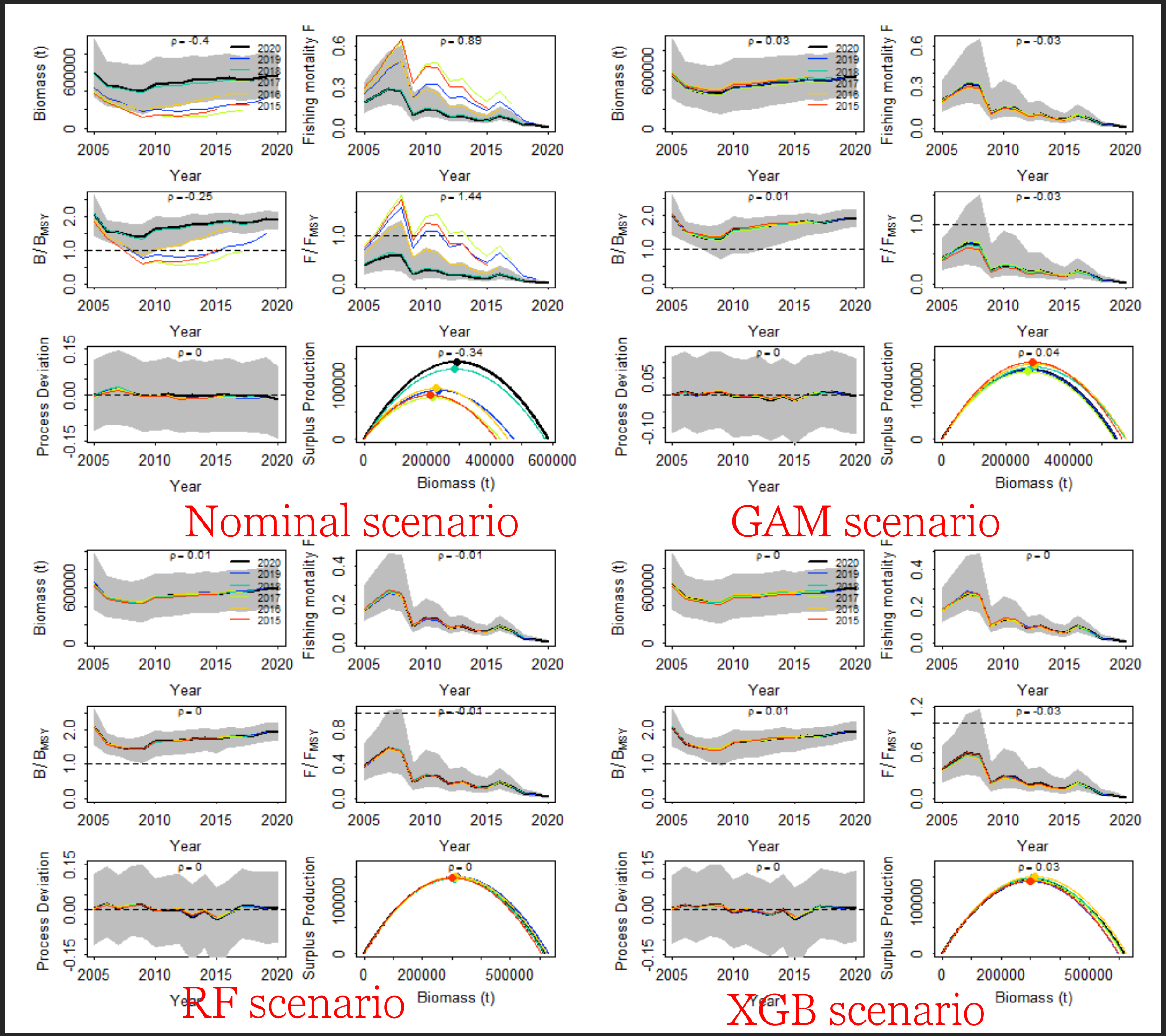


Residual diagnostic plots of CPUE indices

JABBA model diagnostics for winter-sprint cohort

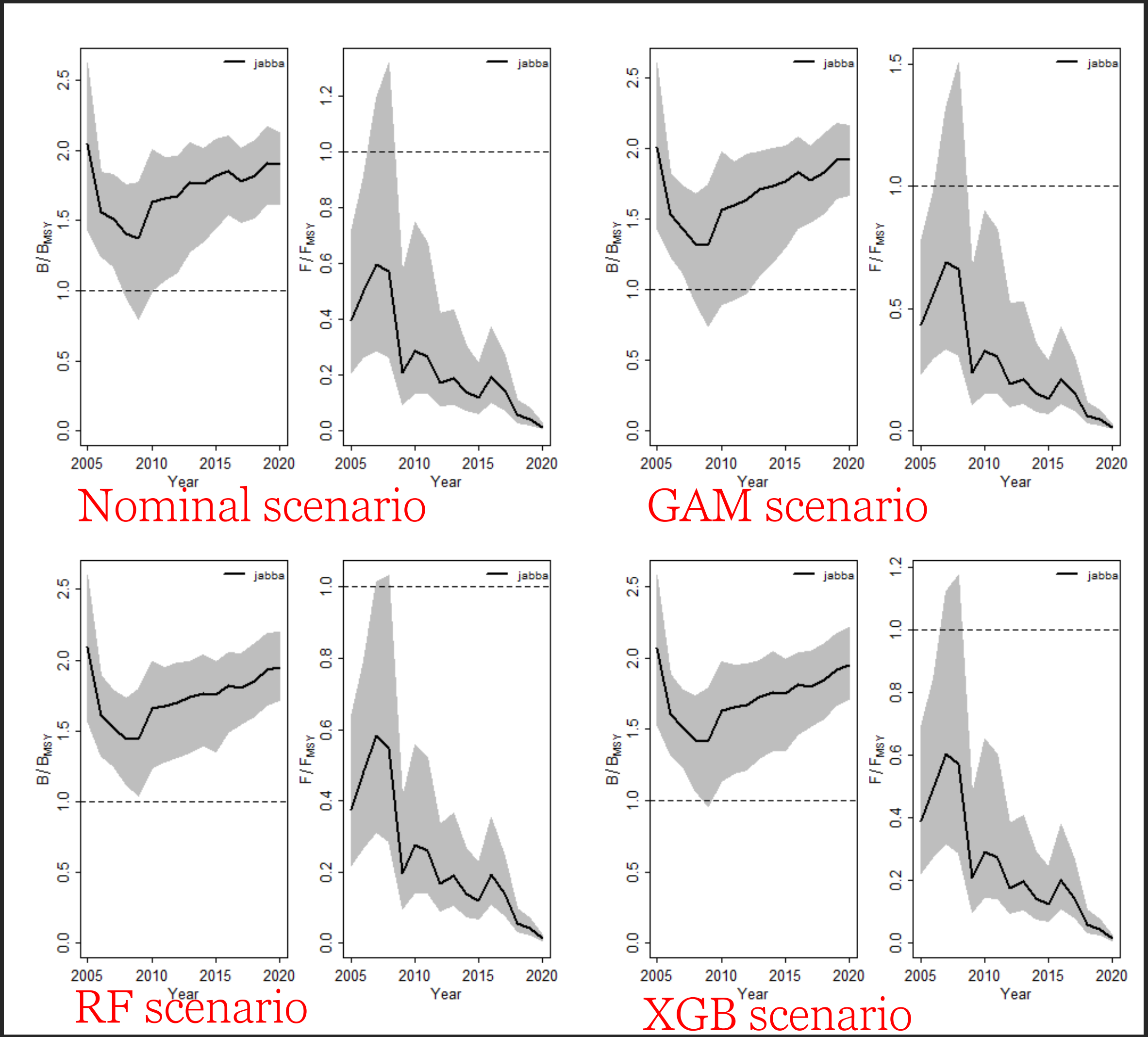


JABBA model diagnostics for winter-sprint cohort

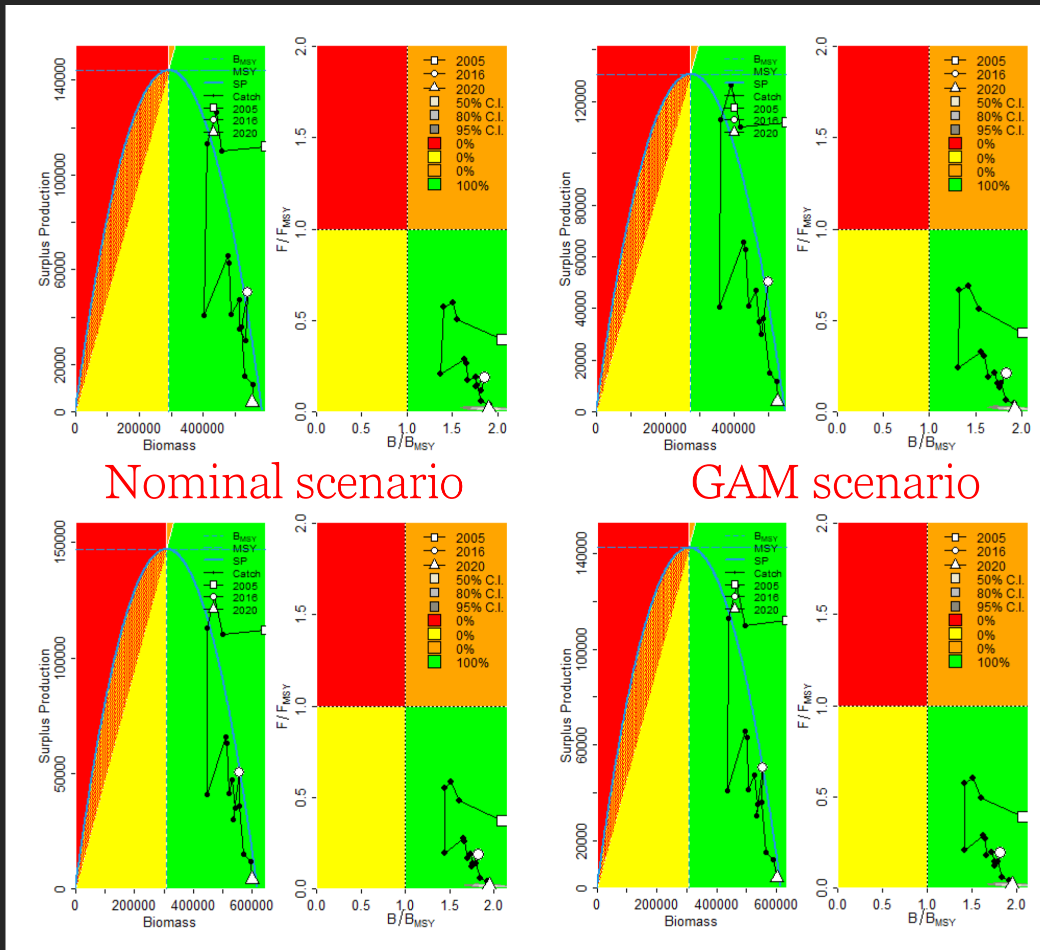


- Retropective analysis

JABBA mode results for winter-sprint cohort



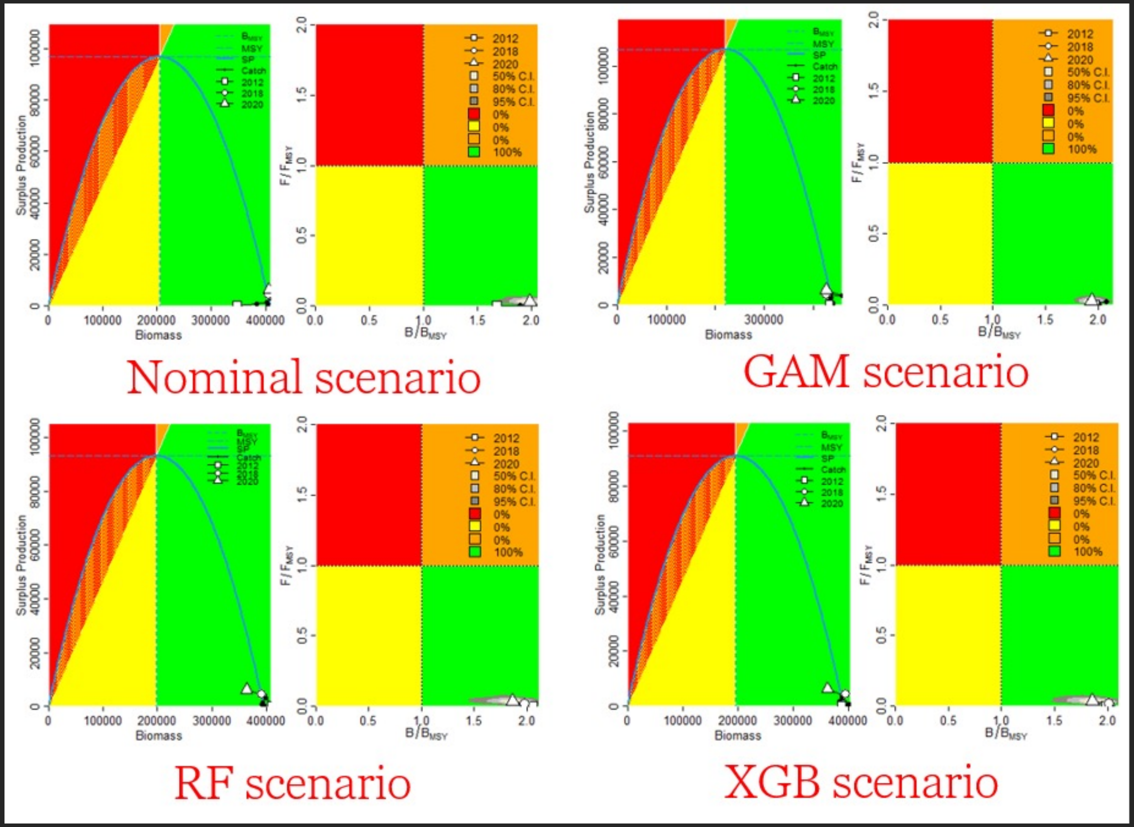
JABBA model results for winter-spring cohort



RF scenario

XGB scenario

JABBA model results for autumn cohort



Similar results of model fitting and diagnostics for autumn cohort.

3. Abundance projection

Materials and Methods

- Environmental data under five Shared Socioeconomic Pathways (SSP) scenarios (119, 126, 245, 370, 585) of CMIP6 during 1900-2100.

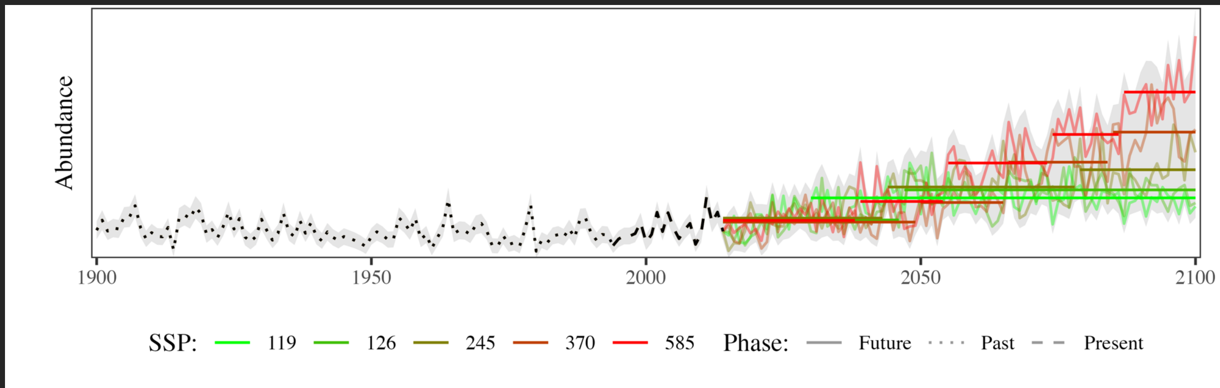
（https://esgf-node.llnl.gov/projects/esgf-llnl/）

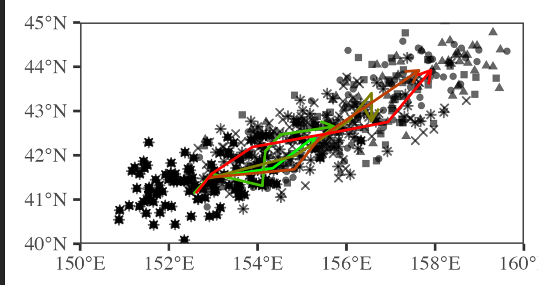
- Using final XGB models to project winter spring cohort

- Two metrics: 1: annual mean abundance,

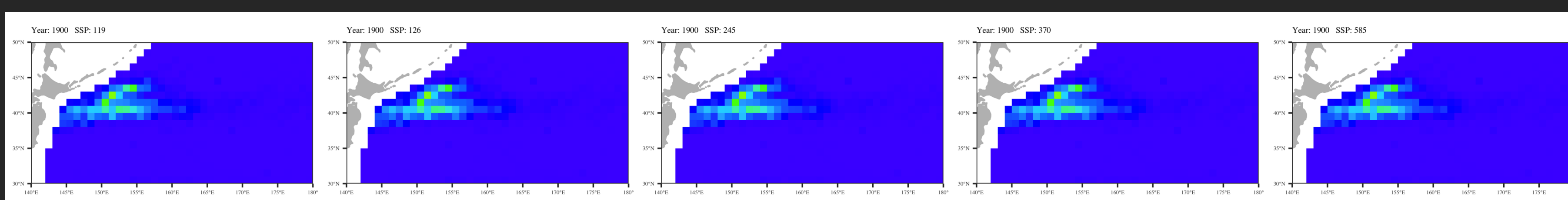
  2: annual gravity of abundance

Results





- Should be optimistic about trend of abundance.
- However, be pessimistic about the abundance in the traditional fishing ground



Conclusion

1. ENSO events (Nino indices) heavily affect the distribution and the abundance (locally and globally) of NFS in three spatiotemporal models, thus Nino indices and related environmental factors should be incorporated strongly in the SA models.
2. Results of SA showed that the NFS are in healthy status (no overfishing and overfished), though annual fluctuation of biomass occurred.
3. Projection showed that climate change seems to be beneficial for the NFS, but the biomass would decrease in traditional fishing ground, this increases the difficulty of fishing in future.

Thanks