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# 水産資源管理における新規加入量予測の有効性の評価

Evaluation of effectiveness of recruitment prediction in fisheries management

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# INTRODUCTION

It is well known that recruitments of many marine organisms are affected by oceanographic environments and largely fluctuate. For example, some part of recruitments of Japanese sardine (*Sardinops melanostictus*) and Japanese mackerel (*Scomber japonicas*) are known to be related to SST (sea surface temperature) in their nursery areas (Noto and Yasuda, 1999; Yatsu et al., 2005). There are many studies on relationships between ocean environments and recruitments. These studies focused on finding environmental factors which correlate with recruitment and discuss the mechanism by which the environmental factors affect recruitments. Although most of these studies set their goal are improvement of fisheries managements, there are few cases in which managers incorporate environmental index in setting catch quota to predict recruitment. In Japan, Acceptable Biological Catch (ABC) are determined by computer simulation that do not include environmental factor. Recruitment is modeled as a resample from past recruitments or derived from stock-recruitment relationship with random variation.

Longtime field surveys are needed to reveal relationships between environment and recruitment. On the other hand, we can easily discuss how recruitment prediction improves the management performance by the model analysis.

From point of view of cost-benefit, values of these studies should be evaluated by models in advance.

Some studies evaluated improvements of fisheries managements by recruitment predictions. The results were inconsistent. De Oliveira and Butterworth (2005) showed benefit of recruitment prediction by using environmental indices in anchovy fishery in Bay of Biscay. Agnew et al. (2002) showed recruitment prediction is useful for management of squid stocks. On the other hand, Basson (1999) showed recruitment prediction is not useful for management of cod stock. The past studies suggested that the effects of recruitment prediction seem to be different by species. It should be profitable to discuss the condition in which recruitment prediction is useful.

These studies concerned confined catch control rules such as constant catch rate strategies in which a certain portion of biomass is exploited independently of stock biomass. However, decreasing fishing mortality with decreased stock biomass is reasonable way of fisheries managements. Recently, fisheries management based on catch control rule (CR) becomes popular. CR determines fishing mortality as a function of condition factors such as stock biomass. By using CR, we can consider how we should decrease fishing mortality rate with decline of stock biomass. In management procedure (MP) approach (Butterworth, 2007) which is consistent with precautionary approach (FAO, 1996), managers compare wide range of catch control rules(CRs) by simulations and select the best CR to be carried out. In MP approach, managers can tackle uncertainty of recruitment by using a CR which is robust to the uncertainty. Past studies may overestimate the effect of recruitment prediction because they considered less flexible strategies and ignored possibility of selecting robust CRs.

In this study, I evaluated the effect of recruitment prediction based on MP approach and explored key life history parameters which determine the effect of recruitment prediction. I used Japanese common squid (*Todarodes pacificus*), Japanese sardine (*Sardinops melanostictus*) and Walleye pollock (*Theragra chalcogramma*) as examples of an annual fish whose longevity is one-year, short lived pelagic fish, and long-lived demersal fish, respectively. They all are commercially important fish for Japanese fishery and annual stock assessment reports are published by fisheries research agency ( in *Marine fisheries stock assessment and evaluation for Japanese waters*, http://abchan.job.affrc.go.jp/index.html). I used stock assessment reports published in 2007 whose fiscal year is 2006/2007.

# MATERIALS and METHODS

I used the population dynamics models in the stock assessment reports by Fisheries Research Agency. Parameters in models were derived from the stock assessment reports (Table 1). There are two common squid stocks, four pollock stocks and two sardine stocks in Japan. The parameters are different by stocks. I used the parameter of the biggest population of the each species (Autumn birthed stock of common squid and Pacific stocks of sardine and pollock).

Table 1. List of parameters. B/H in SRR column means Beverton and Holt Stock-Recruitment relationships. Equations for these SSR are $N_{0,y} = a * SSB_y/(1 + b * SSB_y)$ for B/H SRR and $N_{0,y} = a * SSB_y * e^{-b*SSB_y}$ for Ricker SRR respectively. $W_a$, $s_a$, and $Q_a$ indicate weight, selectivity ,and maturity at age ,respectively. M indicates natural mortality. $\sigma_{rec}$ indicates variation of SRR in equ.5,7.

| | Japanese common squid | Japanese sardine | Walleye pollock |
|---|---|---|---|
| $W_a$ (g) | 280 | (26,64,87,107,122,140) | (41,126,233,393,482,534,604,660,756) |
| $s_a$ | N/A | 1 for all age | (0.040,0.032,0.085,0.209,0.358,0.466,0.706,1,1) |
| M | 0.6 | 0.4 for all age | (0.4,0.35,0.3,0.25,0.25,0.25,0.25,0.25,0.25) |
| $Q_a$ | N/A | (0,0.5,1,1,1,1) | (0,0,0,0.2,0.8,0.9,1,1,1) |
| $\sigma_{rec}$ | 0.32 | 1.07 | 0.52 |
| SRR | B/H | B/H | Ricker |
| Parameter in SRR:a | 0.42 (million/ton) | 18 (thousand/ton) | 20 (thousand/ton) |
| Parameter in SRR: b | $7.3 * 10^{-4}$ (/100ton) | $1.0 * 10^{-4}$ (/1000ton) | $3.8 * 10^{-6}$ (/ton) |

## Population dynamics models

*・sardine and pollock*

Age structured population models were used. It is assumed that fishing occurs in the middle of the year and spawning occurs in the beginning of the year. Basic population dynamics were modeled as follows:

$$N_{a+1,y+1} = N_{a,y}e^{-M} - C_{a,y}e^{-\frac{M}{2}} \qquad (1)$$

where $N_{a,y}$ and $C_{a,y}$ are numbers at age and caught numbers at age in year *y* respectively and M is natural mortality.

$$C_{a,y} = \min\left(\frac{CQ_{a,y}}{W_a}, N_{a,y}e^{-M/2}\right) \qquad (2)$$

$CQ_{a,y}$ is Catch Quota at age in year *y* which is calculated from catch Control Rules below. $C_{a,y}$ cannot exceed the number of individuals in the middle of the year.

$$SSB_y = \sum N_{a,y}Q_aW_a \qquad (3)$$

$SSB_y$ is spawning stock biomass in f year y and $Q_a$ is mutuality at age. Number of recruitments was modeled as follows:

$$N_{0,y} = f(SSB_y)e^{\varepsilon} \qquad (4)$$

$$\varepsilon \sim N(0, \sigma_{rec}^2) \qquad (5)$$

where f() is stock-recruitment relationship (SRR, Figure 1 and Table 1) such as Beverton-Holt and Ricker. $e^{\varepsilon}$ is process error term estimated from actual data, whose logarithm is normally distributed with mean 0 and standard deviation $\sigma_{rec}$.

Figure 1 Stock-recruitment relationships for Japanese common squid (a), Japanese sardine (b) and Walleye pollock (c). Solid lines represent the estimated Stock-recruitment curves.

・*Japanese common squid*

Model for Japanese common squid is different from those for other stocks because it is annual stock without age structure. It is assumed that fishing occurs also in the middle of the year but spawning occurs in the end of the year. The population dynamics of common squid was modeled as follows:

$$N_y = f(SSB_{y-1})e^{\varepsilon} \qquad (6)$$

$$\varepsilon \sim N(0, \sigma^2_{rec}) \qquad (7)$$

where $N_y$ is number of individuals in year $y$ and calculated as a function of spawning stock biomass of the previous year ($SSB_{y-1}$). SSB of squid is modeled as follows,

$$SSB_y = N_y e^{-M} W - C_y W e^{-M/2} \qquad (8)$$

The density dependent effects in sardine and pollock's SRRs were weak (Fig.1 (b) (c)). Thus, SSB of sardine and pollock increased to unrealistic level under low fishing mortality. Because most part of data of both stocks is from low population abundance level era, the estimated SRR may fail to express density dependence effect. Therefore I restricted SSB not to exceed historical maximum quantity since 1976 for sardine and 1981 for pollock(15million tons for sardine and 350 thousand tons for pollock).

## Recruitment prediction using environmental index

The parameter $\varepsilon$ in equs.4 and 6 indicates the deviation of recruitment from SRR. I assumed that some part of $\varepsilon$ can be explained by environmental index. I divided $\varepsilon$ into two parts, the part which can be explained by environmental index and the part which cannot be explained by the index. The relationship between the environmental index and deviations of recruitment from SRR is modeled after De Oliveira et al. (2005),

$$\varepsilon = \mathrm{R}\sigma_{\mathrm{rec}}\mathrm{Env}_y + \sqrt{1-\mathrm{R}^2}\sigma_{\mathrm{rec}}\varepsilon_y^{\mathrm{ran}} \quad \sim \mathrm{N}(0, \sigma_{\mathrm{rec}}^2) \qquad (9)$$

$$\varepsilon_y^{\mathrm{ran}} \sim \mathrm{N}(0,1) \qquad (10)$$

$$\mathrm{Env}_y \sim \mathrm{N}(0,1) \qquad (11)$$

R is correlation coefficient between $\varepsilon$ and $\mathrm{Env}_y$. The first term of right side of equation (9) is the recruitment deviation from SRR which can be explained by environmental index and the second term is the deviation which cannot be explained. $\mathrm{R}^2$ below is the amount of variations of $\varepsilon$ explained by $\mathrm{Env}_y$. As showed above (in equ (4) and (6)), recruitment can be divided into SRR and deviations from SRR. I assumed managers predict recruitment using SRR and $\hat{\varepsilon}$ which is the predictable deviation of recruitment from SRR by using environmental index $\mathrm{Env}_y$. The recruitment deviation from SRR which can be predicted by managers is,

$$\hat{\varepsilon} = \mathrm{R}\sigma_{\mathrm{rec}}\mathrm{Env}_{\mathrm{y}} \qquad (12)$$

The larger $R^2$ is, the more accurately recruitment can be predicted. Five values of $R^2$ were trialed ($R^2$=0, 0.25, 0.5, 0.75, 1). I assumed that managers know true SRR, recruitment variation ($\sigma_{\mathrm{rec}}$) and the amount of variation which can be explained by environmental index (R). Thus, recruitment predictions for each species were modeled as follows:

for common squid,

$$\widehat{\mathrm{N}_y} = \mathrm{f}(\widehat{\mathrm{SSB}_{y-1}})\mathrm{e}^{\hat{\varepsilon}} \qquad (13)$$

for sardine and Pollock,

$$\widehat{\mathrm{N}_{0,y}} = \mathrm{f}(\widehat{\mathrm{SSB}_y})\mathrm{e}^{\hat{\varepsilon}} \qquad (14)$$

where $\widehat{\mathrm{N}_y}$ and $\widehat{\mathrm{N}_{0,y}}$ are predicted number of recruitments (note that common squid is an annual stock) and $\widehat{\mathrm{SSB}_y}$ is estimated spawning stock biomass.

## Stock biomass estimation of non-recruitment ages for sardine and pollock

Stock biomass estimation is used for decision making in Control Rules. Stock biomass estimation of newly recruited cohort was modeled in the previous section. Stock biomass estimation of cohorts that already recruited previous year for sardine and pollock was modeled as follows. Abundance of sardine and pollock are estimated by VPA (Virtual Population Analysis). The estimation error of VPA has specific character. The abundance of young cohort is highly uncertain, because there is little information available. The estimation error of a cohort decreases with time, because the data from fisheries and research monitoring become available. I assumed estimation bias of $\widehat{N_{0,y}}$ from $N_{0,y}$ decreases as the cohort get older by α each year. This assumption is modeled as follows:

$$\widehat{N_{0,y}} = (1 + \gamma_y)N_{0,y} \qquad \gamma_y \geq -1 \qquad (15)$$

$$\widehat{N_{\iota,y+\iota}} = (1 + \alpha^i\gamma_y)N_{i,y+i} \qquad \text{for i=1,2,3...} \qquad (16)$$

$\gamma_y$ is estimation bias resulted from recruitment prediction. $\gamma_y$ which is less than 0 means recruitment is underestimated in recruitment prediction. On the other hand, $\gamma_y$ larger than 0 means recruitment is overestimated in recruitment prediction. An overestimated (underestimated) cohort when it recruited continues to be overestimated (underestimated) but the degree of overestimation (underestimation) decreases. The degree of estimation bias decreases is represented as α. α can be interpreted as the effect of fisheries data and monitoring after recruitment such as acoustic surveys. The more intensively stocks are monitored after recruitment, the less $\alpha$ is. I trialed three $\alpha$ (1, 0.75, 0.5). When $\alpha = 1$, the accuracy of stock biomass estimation does not improve after recruitment, and completely depend on the accuracy of recruitment prediction. On the other hand, when $\alpha = 0.5$, the estimation bias is halved each year and the accuracy of stock biomass estimation for old ages are good regardless of the accuracy of recruitment prediction. Results using $\alpha = 0.75$ will be shown in figures as intermediate case and results for other $\alpha$ were summarized in Table 2.

## Catch Control Rules (CRs)

I used CRs which consist of three lines (Katsukawa, 2004, Figure 2) . These 3L-CRs is used in Japanese fisheries managements as basic rule in calculating ABC which is

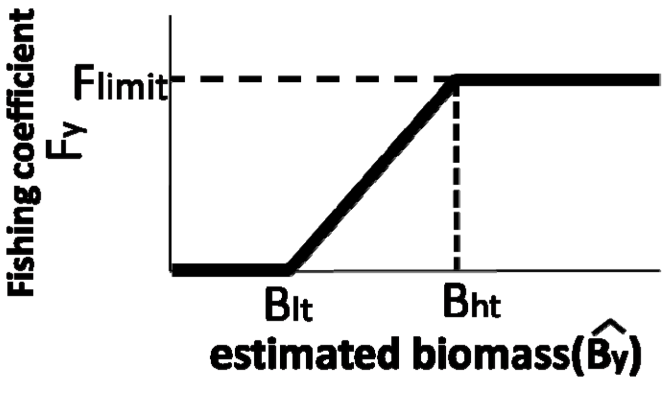


Figure 2 The three line control rule. Fishing mortality coefficient $F_y$ is a function of estimated biomass $\widehat{B_y}$. $B_{lt}$ is the biomass level below which no fishing is allowed. $B_{ht}$ is the biomass level above which fishing pressure is constant ($F_y = F_{limit}$).

a reference of TAC (Fisheries Agency of Japan and Fisheries Research Agency 2008, http://abchan.job.affrc.go.jp/digests19/rule/rule19.pdf). These CRs were determined by the following three parameters: (i) lower threshold biomass level below which no fishing is allowed ($B_{lt}$); (ii) higher threshold biomass level above which fishing mortality is kept constant ($B_{ht}$); and (iii) the value of the fishing mortality coefficient that is applied if biomass is higher than $B_{ht}$($F_{limit}$). The fishing mortality coefficient *F* was determined by the estimated standing stock biomass level $\widehat{B_y}$.

$$\begin{cases} \text{If } \widehat{B_y} \le B_{lt} \text{ then } F_y = 0 \\ \text{If } B_{lt} < \widehat{B_y} \le B_{ht} \text{ then } F_y = F_{limit} \frac{\widehat{B_y} - B_{lt}}{B_{ht} - B_{lt}} \\ \text{If } B_{ht} < \widehat{B_y} \text{ then } F_y = F_{limit} \end{cases} \quad (17)$$

$$F_{a,y} = F_y s_a \quad (18)$$

$$CQ_{a,y} = \widehat{N_{a,y}} e^{-\frac{M}{2} - F_{a,y}} W_a \quad (19)$$

$s_a$ is selectivity at age. Catch quota at age $CQ_{a,y}$ is calculated by multiplying expected biomass in the middle of the year ($\widehat{N_{a,y}} e^{-M/2} W_a$) and catch rate determined by the CR ($e^{F_{a,y}}$). $s_a$ for pollock is derived from the stock assessment report. $s_a$ for sardine in stock assessment report changes largely each year and selectivity for young fish is unrealistically high compare to the old fish. This is thought to be because there are few old fish after stock collapse in early 1990's. Because $s_a$ for young ages in the stock assessment report may be overestimated and mislead results, I set identical selectivity for all ages (1 for all a). This assumption can be justified because most sardine catch are from purse seine fishery which is not size-selective fishery. I also tried $s_a$ in which mature fish are selectively caught as a rational assumption because catching matured and big fish is biologically and economically appropriate. I showed only the results of no selectivity (1 for all ages) because the results of both scenarios were quite similar.

The estimated SSB which is used in SRR in recruitment prediction and estimated biomass which is used in Control Rules are expressed as follows:

for common squid,

$$\widehat{SSB_y} = \widehat{N_y} e^{-M} W - C_y e^{-M/2} \qquad (20)$$

$$\widehat{B_y} = \widehat{N_y} W \qquad (21)$$

for sardine and pollock,

$$\widehat{SSB_y} = \sum \widehat{N_{a,y}} Q_a W_a \qquad (22)$$

$$\widehat{B_y} = \sum \widehat{N_{a,y}} W_a \qquad (23)$$

## Evaluation of CRs

I tested wide range of CRs by changing the above three parameters ($B_{lt}$, $B_{ht}$, $F_{limit}$). The simulated time was 100 years, and I used the results of the last 50 years to eliminate the effects of initial biomass level. The iteration for each CR was 100 times. I used mean of average yield and minimum SSB for 100 iterations as the management performance of each CR. There are many goals in fisheries management and some of them are incompatible. In this work, for simplification, I used maximizing catch and conserving stocks as two major goals. Average yield represents maximization of benefit from fisheries and minimum SSB represents conservation of stocks, respectively. Figure 3 shows a scatter plot of yield and minimum SSB for sardine with $R^2$=0.5 which means half of recruitment deviation from SRR is predictable by environmental index. CRs which record high average yield and minimum SSB can be defined “good” CR (upper right in Fig.3). I defined a CR to be potentially optimal if there was no other CR that marked a higher yield and higher

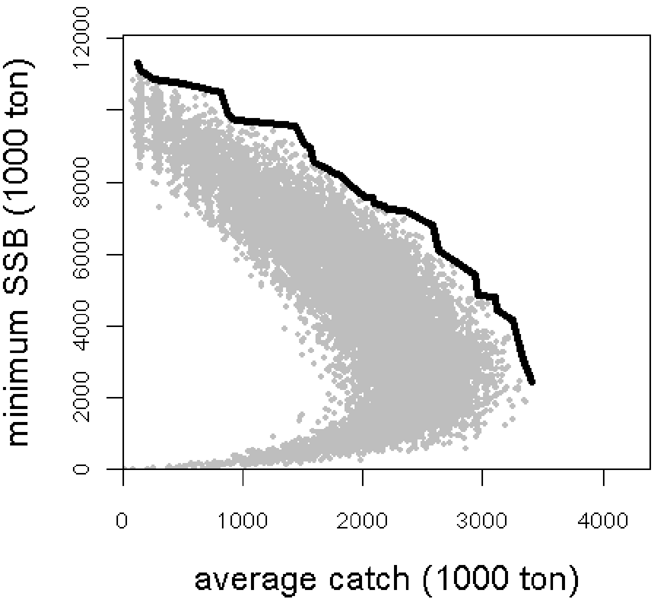


Figure 3 An example of scatterplots of average catch and minimum SSB. This figure is for Japanese sardine when $\mathbf{R^2 = 0.5}$. Every point represents management performance for each CR. The solid line represents potentially optimal CRs when $\mathbf{R^2 = 0}$.

minimum SSB at the same time (solid line in Fig.3). I evaluated the effect of recruitment prediction by looking how much the line which connect potentially optimal CRs was moved toward upper right with better recruitment prediction accuracy (with larger R2).

The effect of recruitment prediction was quantified by the index below:

$$\text{opt\_manage}_{\text{i}} = \max(average\ yield *\ minimum\ SSB)\ when\ \mathrm{R}^2 = i \qquad (22)$$

$$\text{opt\_manage}_{\text{j}} = \max(average\ yield *\ minimum\ SSB)\ when\ \mathrm{R}^2 = j \qquad (23)$$

$$\text{Imp}_{i,j} = \frac{\text{opt\_manage}_i}{\text{opt\_manage}_j} \qquad (24)$$

where $i$ and $j$ are $\mathrm{R}^2$ values and $i > j$. $\text{Imp}_{i,j}$ indicates the degree of management improvement when recruitment prediction accuracy was improved from $\mathrm{R}^2 = j$ to $\mathrm{R}^2 = i$. Large opt_manage is achieved when average yield and minimum SSB are well balanced because doubling average yield is justified only when minimum SSB are kept over half of original size. I used $i$=1 and $j$=0 respectively in results below. The larger $\text{Imp}_{i,j}$ is, the more management performance was improved with better recruitment prediction. $\text{Imp}_{i,j} = 1$ means there was no effect of improved recruitment prediction.

# RESULTS

The effects of recruitment prediction are different between 3 species. Results are summarized in Figure 4 and Table 2. In Japanese common squid, management performance was dramatically improved (Fig.4a, $Imp_{0,1}$=3.24). In Walleye pollock, there was little improvement with better recruitment prediction (Fig.4c, $Imp_{0,1}$ = 1.15). There was intermediate improvement in Japanese sardine (Fig.4b, $Imp_{0,1}$ = 2.77).

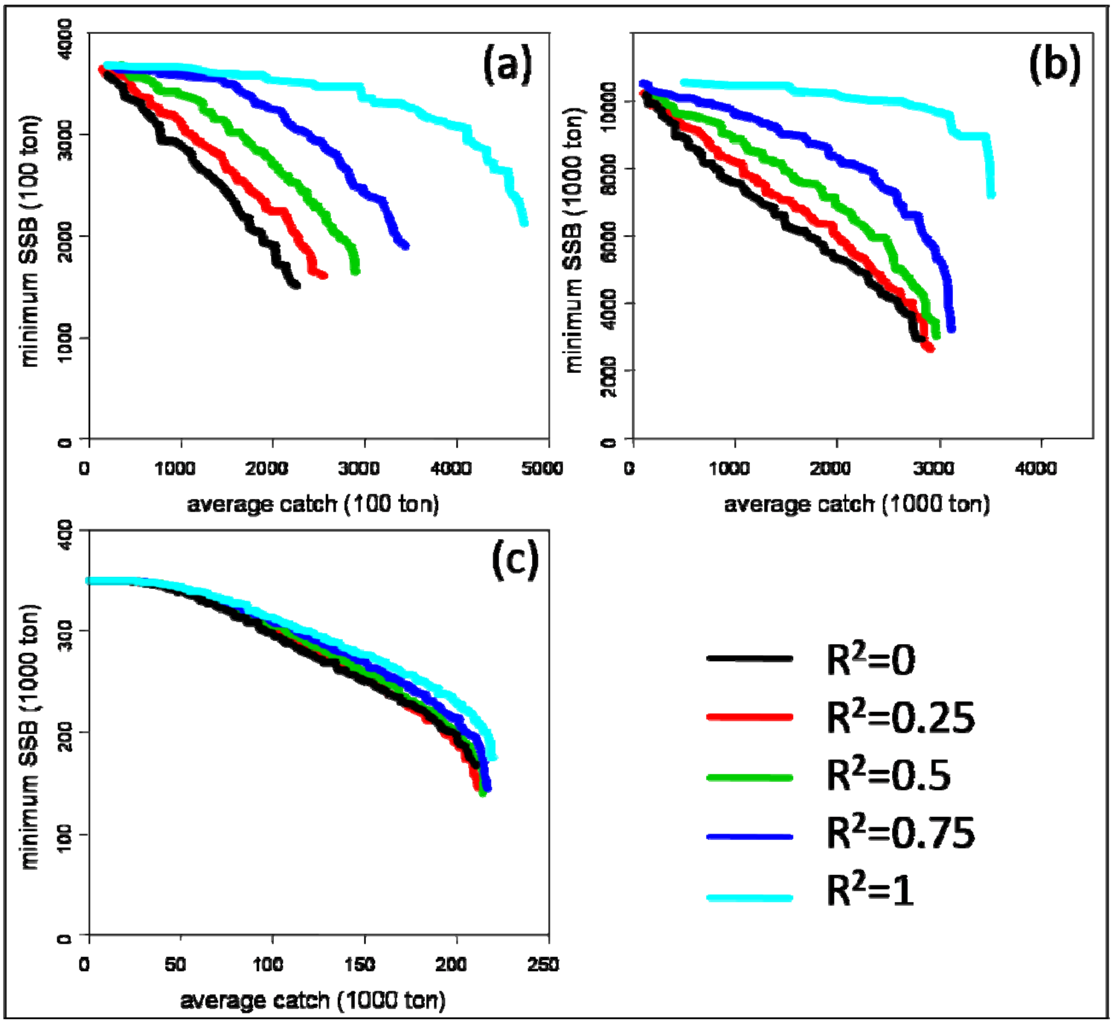


Figure 4 Summary of results for Japanese common squid (a), Japanese sardine (b) and Walleye pollock (c) respectively. Each line represents the potentially optimal CRs in that recruitment prediction accuracy ($R^2$).

Table 2

$\mathrm{Imp}_{0,1}$ for each simulation settings. Values in italic text are for simulation settings used in Figure 4. The second and third rows of sardine are the results of simulation using sardine model with squid's and pollock's recruitment variation respectively. There are no options for $\alpha$ in squid because it does not have age structure.

| | | α | | | |
|---|---|---|---|---|---|
| | | NA | 1 | 0.75 | 0.5 |
| common squid | | *3.24* | − | − | − |
| Japanese sardine | $\sigma_{rec} = 1.07$ | − | 5.12 | *2.77* | 1.49 |
| | $\sigma_{rec} = 0.32$ (squid) | − | 1.55 | 1.26 | 1.06 |
| | $\sigma_{rec} = 0.52$ (pollock) | − | 2.15 | 1.42 | 1.15 |
| Walleye pollock | | − | 1.79 | *1.15* | 0.98 |

## The effect of $\alpha$ (the rate by which stock estimation bias decrease)

The effects of recruitment prediction were less in $\alpha = 0.5$ simulation than in $\alpha = 0.75$ one for both species ($\mathrm{Imp}_{0,1} = 1.49$ for sardine and 0.98 for pollock). On the other hand, that in $\alpha = 1$ were larger than in $\alpha = 0.75$ for both species ($\mathrm{Imp}_{0,1} = 5.12$ for sardine and 1.79 for pollock).

## The effect of $\sigma_{rec}$

There are two feasible life history parameters which make the difference of the effect of recruitment prediction between stocks. One is longevity and the other is magnitude of recruitment variation. To distinguish the effect of magnitude of recruitment variation from that of longevity, I ran simulations of Japanese sardine models with different $\sigma_{rec}$, one is with common squid's $\sigma_{rec}$ and the other is with walleye pollock's $\sigma_{rec}$. The first row of sardine in Table 2 represents $Imp_{0,1}$ with sardine's original $\sigma_{rec}$ and second and third row represent $Imp_{0,1}$ with squid's and pollock's $\sigma_{rec}$ respectively. The larger $\sigma_{rec}$ was, the larger $Imp_{0,1}$ of each simulation settings was. Comparing the $Imp_{0,1}$ for common squid and that for sardine model with the same $\sigma_{rec}$ as squid, $Imp_{0,1}$ for squid was larger than that for sardine (3.24 and 1.26 respectively). $Imp_{0,1}$ for sardine model with pollock's $\sigma_{rec}$ was larger than that for pollock.

# DISCUSSION

## Key life histories which determine effectiveness of recruitment predictions

Japanese common squid whose management performance was dramatically improved is annual stock. This result is reasonable because all of the Japanese common squid population are newly recruited individuals. On the other hand, there was little improvement for walleye pollock which is long lived and late matured fish and main target are old fish. Japanese sardine has intermediate life history and the improvement was also intermediate.

The results of same stock's model with different recruitment variation magnitude showed that the performance improvement by recruitment prediction is greater for the larger recruitment variation. Then results of different stocks' model with same recruitment variation showed that the performance improvement by recruitment prediction is greater for shorter longevity. These results suggest that short lived and highly recruitment fluctuated species have large potential of improved management performance with better recruitment prediction accuracy. These results are consistent with past case studies and I integrated different species' results in a same simulation manner and enabled sound comparison.

## Comparison between recruitment prediction and monitoring after recruitment

Stock size estimation error can be decreased not only by recruitment prediction, but also monitoring after recruitment. I assumed estimation error generated in the recruitment prediction decrease as the cohort gets old. The rate by which stock estimation bias decreases is $\alpha$. Small $\alpha$ may be achieved if the stock is monitored extensively after recruitment for example by acoustic surveys. Thus, in our simulations, estimation accuracies for older ages depend on both recruitment prediction accuracy and $\alpha$. If there is a good monitoring system and $\alpha$ is small (e.g. 0.5), estimation accuracies for older ages are good even if that for recruitment is bad. On the other hand, estimation accuracies for older ages directly reflect that for recruitment when $\alpha = 1$.

In general, it is not necessary to exploit young cohorts, because weight and price of fish individual increase with age. If selectivity is concentrated on old cohorts, the accuracy of stock size estimation for old cohorts becomes important. In such case, small value of $\alpha$ is preferable rather than recruitment prediction. When $\alpha = 0.5$, estimation for old ages are precise regardless of recruitment prediction accuracy. Therefore, there was little improvement in the performance of fisheries management by good recruitment prediction ($Imp_{0,1}$ were 1.49 and 0.98 for sardine and pollock respectively). When $\alpha = 1$, there was no improvement in estimation accuracy by aging. In this case, errors in the recruitment prediction remains whole life, thus performance of fisheries management largely depends on recruitment prediction and was improved dramatically with better recruitment prediction accuracy ($Imp_{0,1}$ were 5.12 and 1.79 for sardine and pollock respectively).

These results suggest that fisheries management can be improved by enhancing monitoring after recruitment. For long lived species like pollock, monitoring after recruitment seems to be more important than recruitment prediction. For species with moderate longevity, such as sardine, monitoring after recruitment is good alternative to the recruitment forecast. Managers should compare cost-benefit and feasibility of recruitment prediction and monitoring after recruitment.

## Quantitative evaluation of effects of recruitment prediction

Appropriate management performance measures depend on the management objectives. In general, the goal of fisheries management is maximizing fisheries production while minimizing biological risk of overfishing. I used average catch and minimum SSB for simplicity as measures of management goal. In real fisheries management, we have to consider many other management performance measures such as yearly catch variation and risk of stock collapse.

In this work, I defined CR which maximizes the product of average catch and minimum SSB was the optimal. That is because I considered that balancing average yield and minimum SSB would be preferred in real management. If this is not the case, the manager has to use other criterion which is suitable for object of the fisheries management. There may be other quantitative index such as index using not products but distance from the origin in scatter plots. The index using distance from origin in scatter plots use to be maximized by CR which achieve high average yield or minimum SSB sacrificing the other.

## Proposal to fisheries managements

In Japan, many economically important species, like chub mackerel and Japanese sardine, have been heavily overexploited. There are many rooms to improve management performances by decreasing fishing mortality. Before considering to use recruitment prediction, manager should stop overfishing and use potentially optimal CRs.

Researches for recruitment prediction need much time and money. Brander

(2003) pointed out three prerequisites of environmental index for recruitment prediction: (i) the effect should be significant, (ii) there should be a credible explanation of the process by which the environmental factor acts, (iii) the environmental information must be available in a timely and cost-effective form. It may be difficult to find such indexes. Furthermore, it is very uncertain how much the accuracy of recruitment prediction would be improved. In comparison with this, changing CR needs less cost and time.

Both Japanese sardine and chub mackerel have nearly collapsed after successive year of recruitment failure and successive high fishing pressures. There is no strict catch control rule in Japan and fishing mortality of sardine increased as stock biomass decreased (Fig. 5). Thus, age compositions for these fish are very truncated to young fish and most catch consists of immature 0 or 1 age fish (Fig. 6). Consequently the amounts of recruitment have serious impact on the fisheries and recruitment prediction accuracies usually become

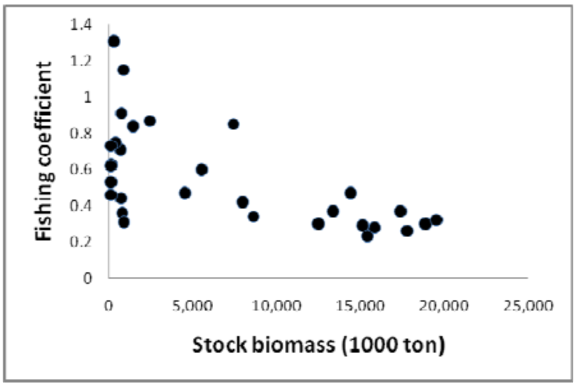


Figure 5 Fishing coefficients and stock biomass of sardine during 1977~2006. Fishing coefficients are average of those of all ages.

controversial issues. However, Fig. 7 shows that management performance of Japanese sardine can be dramatically improved by adopting appropriate CR even if manager cannot predict recruitment precisely ($R^2$=0) and the accuracy of prediction cannot be improved. This indicates that the necessity of recruitment prediction is overstated in the current controversy. Considering there being no promising environmental index for recruitment prediction and high fishing pressure resulting in recruitment and spawning overfishing, managers and fishing industries should decrease fishing pressure and mainly catch old fish before discussing recruitment predictions.

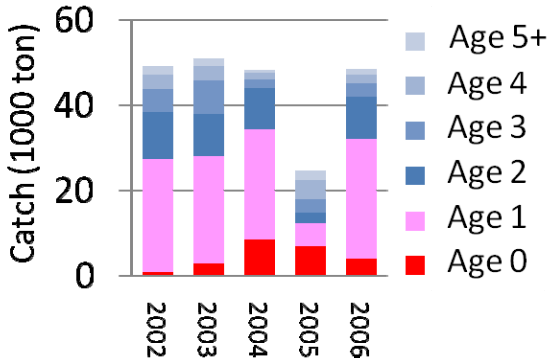


Figure 6 Catch at age of sardine in recent years.

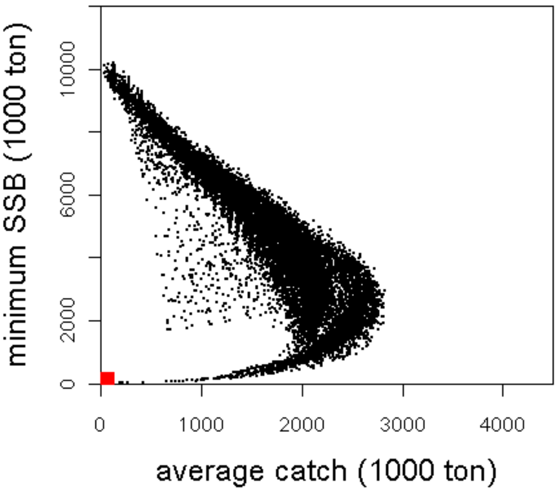


Figure 7 Management performances of CRs when $R^2$=0 (small circles) and that of recent years (2002~2006, red square).

# CONCLUSIONS

This study showed that recruitment prediction is potentially useful forfisheries management especially for the stock with short longevity and large recruitment fluctuation. I also found that developing a good monitoring system after recruitment can also improve management performance.

Many fish stock in the Japanese EEZ are heavily over exploited. There are many rooms to improve fisheries production just by reducing fishing mortality. At the first step, fishing mortality should be declined to the appropriate level.　If the further improvement in management performance is preferable, we should consider to use recruitment prediction. There are many alternatives, such as monitoring after recruitment. We have to estimate which is the most effective

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