Evaluation of the predictability of fishing forecasts using information theory

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Abstract

The catch forecast is important for fisheries activities. Previous research has tried to improve the forecast accuracy. However the forecast accuracy does not directly correspond to the forecast benefit and an inaccurate forecast could be more beneficial than accurate one. Herein as part of the forecast utility, predictability was evaluated using information theory. Mutual information *MI* was used as index of predictability. *MI* denotes a reduction in uncertainty when a forecast is taken into account. Adding this, hit ratio *HR* and relative entropy *R* were used as consistency indices. *HR* denotes a frequency that the predicted values consist with the actual values, and *R* denotes the distance of the probability distribution between the actual and forecasted fishing conditions. As an application, the long-term change-ratio forecasts in 1972–2009 (n=36), short-term change-ratio forecasts (n=34), and short-term level forecasts (n=33) in 2004–2009 of Pacific saury *Cololabis saira* fishery were evaluated. The order of *MI*, *HR*, and *R* varied between these forecasts, indicating that forecast predictability and consistency do not correspond. Monitoring multiple indices would improve forecasting systems.

Keywords fishing forecast, forecast evaluation, information theory, mutual information, Pacific saury, relative entropy

Introduction

One of the main goals of fishery investigations is to forecast fish stock level and provide recommendations to control fishing operations [1]. Studies of the recruitment forecast have been on-going for more than a century [2], and many empirical researches has been reported [3-6].

The catch forecast is widely used for fishery activities, including the efficient utilization of resources and planning of fishing operations [7, 8]. Previous researches on catch forecast has been tried to improve the accuracy; that is, the predicted forecast consists with the actual values. Accuracy could be described as indices of consistency [e.g., hit ratio (*HR*) [9] or mean absolute error (*MAE*) [10]], and has been well researched as a criterion for the goodness of forecast.

On the other hand, accuracy does not directly correspond to beneficial forecast [11]. For example, the population forecast of a marine resource with a small population fluctuation could easily be accurate. Moreover, if a too wide forecast statement such as “the catch of this year will be between one ton and one billion tons” absolutely hit but obviously unbeneficial. Thus, an accurate forecast does not necessarily mean a beneficial forecast. Conversely, an inaccurate forecast could be more beneficial than accurate one. Hence, the improvement of the forecasts should aim for a beneficial forecast rather than an accurate forecast. Previous works rarely refer to forecast criterion except accuracy, and the exceptional examples [8] were effective only for specific cases.

In the current research, predictability was defined as the extent of difference between prior probability

distributions and forecasted probability distributions, followed to DelSole [12]. By using this definition, a forecast statement "probability of becoming the catch will be between one ton and one billion tons is 100%" is regarded as no predictability forecast. Obviously prior probability distribution is as follows

$$\begin{cases} p(Catch < 1) & = 0.0 \\ p(1 \le Catch \le 1000000000) & = 1.0 \\ p(1000000000 < Catch) & = 0.0 \end{cases} \tag{1}$$

where $p()$ is probability. When the forecast "the catch of this year will be between one ton and one billion tons" is taken into account, forecasted probability distribution are exactly equal to the prior distribution. Therefore this forecast has not got any predictability. When a forecast predicted a result unobvious situation, predictability of forecast is high.

The amount of information [13] could be an index of the forecast predictability. Shannon quantified information as a reduction in uncertainty. If a forecast predicts an obvious situation, it does not contain any information because the uncertainty is not reduced. By using information theory, the forecast predictability can simply be quantified. Adding this, information theory can quantify difference of probability distribution, so information theory can be used as not only as predictability index but also as consistency index. Information indices would contribute to improved forecasts.

The Pacific saury *Cololabis saira* fishing forecast can easily distinguish between true and false forecasts due to the rich datasets. By comparing each index for several Pacific saury fishing forecasts, the difference between forecast accuracy and forecast information can be described quantitatively.

On this basis, the purpose of the current study was to apply the evaluation of the predictability to the fishing forecasts. Consistency indices were also calculated and compared to the predictability. The procedure to

improve forecasts were proposed and discussed based on the results.

Materials and methods

Information entropy, conditional entropy and mutual information

Predictability and consistency indices for three types of forecasts of Pacific saury were calculated to evaluate the forecasts. All scores are applicable to quantitative forecasts but were described for categorical forecast because of the easy understanding for the readers.

As an index of the predictability, mutual information (*MI*) [13, 14] was calculated. *MI* is described by information entropy $H(A)$ [13] and conditional entropy $H(A|F)$ [13].

In the current research, information entropy was calculated as

$$H(A) = -\sum_{j=1}^{3} p(a_j)\log p(a_j) \tag{2}$$

The notations were defined in Table 1. A was actual fishing condition $(a_j \in A)$. (a_1, a_2, a_3) were defined as ("actual increasing", "actual stable", "actual decreasing") for the change-ratio forecast, or ("actual large", "actual medium", "actual small") for the level forecast respectively (Table 1).

$H(A)$ was the entropy of actual fishing condition A. When $p(a_j)$ was naught, $p(a_j)\log p(a_j)$ was assumed to be naught. In the current study, the base of the logarithm was set to two and the entropy is expressed in the unit "bits", following traditional information theory [13]. Information entropy is high when uncertainty is high. When the actual fishing condition does not have any uncertainty, in other words $H(A)$ equals to naught, it is not necessary to use a forecast.

In the current research, conditional entropy was calculated as

$$H(A \mid F) = -\sum_{i=1}^{3}\sum_{j=1}^{3} p(a_j, f_i)\log p(a_j \mid f_i) \tag{3}$$

where F was forecasted fishing condition $(f_i \in F)$. (f_1, f_2, f_3) were defined as ("forecast increasing", "forecast stable", "forecast decreasing") for the change-ratio forecast, and ("forecast large", "forecast medium", "forecast small") for the level forecast respectively (Table 1). $p(a_j, f_i)$ and $p(a_j \mid f_i)$ were the joint probability and conditional probability, respectively. $H(A|F)$ was the conditional entropy of the actual fishing condition A and fishing forecast F. Conditional entropy indicated the uncertainty of the actual fishing condition subject to a given fishing forecast. If the conditional entropy of a forecast was equal to the information entropy of the actual fishing condition, this forecast had not got any information because this forecast did not decrease the uncertainty.

In the current research, *MI* was calculated as

$$\begin{aligned} MI &= \sum_{i=1}^{3}\sum_{j=1}^{3} p(a_j, f_i)\log\left[\frac{p(a_j, f_i)}{p(a_j)p(f_i)}\right] \\ &= -\sum_{i=1}^{3} p(a_j)\log p(a_j) + \sum_{i=1}^{3}\sum_{j=1}^{3} p(a_j, f_i)\log p(a_j \mid f_i) \\ &= H(A) - H(A \mid F) \end{aligned} \tag{4}$$

MI was the reduction in the uncertainty of the actual fishing condition caused by a forecast. In other words, *MI* measures the entropy difference between the prior and forecasted fishing condition. Therefore, *MI* can be an index of the predictability [12]. When *MI* was high, the prediction procedure had got a high predictability [15].

MI is symmetry for A and F. Therefore, the following equation is equivalent to equation (4).

$$MI = H(F) - H(F \mid A) \tag{5}$$

However, it would be recommended to use equation (4). Object of the interest would be actual fishing condition for fishers. Equation (4) described change of uncertainty of actual fishing condition directly. In the current research, conditional entropy $H(A \mid F)$ which used in equation (4) was used.

Hit ratio

The hit ratio *HR* and relative entropy *R* [14] were calculated as consistency indices. *HR* described the accuracy of a forecast, and was defined as the probability that a forecast consists with the actual level or the actual change ratio. It was calculated as

$$HR = p(a_1, f_1) + p(a_2, f_2) + p(a_3, f_3) \tag{6}$$

Relative entropy

In the current research, relative entropy *R* was calculated as

$$R = \sum_{k=1}^{3} p(a_k) \log \frac{p(a_k)}{p(f_k)} \tag{7}$$

When $p(a_k)$ was naught, $p(a_k)\log[p(a_k)/p(f_k)]$ was defined as naught, but when $p(f_k)$ was naught, $p(a_k)\log[p(a_k)/p(f_k)]$ was defined as infinity. *R* is also called as Kullback-Leibler divergence [16]. Generally,

R is always non-negative and is naught if and only if two distributions are equivalence. Therefore, R indicates the extent of distance between two probability distributions [14]. For example, Akaike's Information Criterion (AIC) [17] used R for comparing between true probability distribution and probability distribution made by statistical models.

In the current study, R was used as an index of the consistency of the probability distribution of the actual and forecasted fishing condition, measuring the distance between them. For example, although "actual large" frequently occurs in the actual fishing condition, if a forecast frequently predicts "forecast small", then R will be high.

In the current study, MI was calculated as an index of predictability, and HR and R were calculated as consistency indices. MI measured the reduction in the uncertainty using a forecast. HR measured the consistency of the forecast with the actual fishing conditions. R measured the extent of the distance between the probability distribution of the actual and forecasted fishing conditions.

Additionally, $H(A)$ and $H(A|F)$ were used as subsidiary indices. $H(A)$ was an index of the uncertainty in the actual fishing condition. $H(A|F)$ indicated the uncertainty of the actual fishing condition subject to a given fishing forecast.

Numerical example

For the understanding of the characters of the indices, four illustrative example data sets were provided in Tables

2, and the calculated indices were shown in Table 3. The first data set (Table 2a) was an example of a good forecast, which had got high *HR* and *MI*, and a low *R* value. The second data set (Table 2b) was an example of bad forecast where *MI* and *HR* were low. This forecast had got little information and was inaccurate. The third data set (Table 2c) had got highest *MI* and a fairly high *HR* than Table 2b, but was a poor forecast. In this situation, "Actual 3" occurred when "Forecast 1" was posted, and "Actual 1" occurred when "Forecast 3" was posted. It would be difficult to make appropriate decisions in this situation. Although the forecast did not hit, theoretically it had got a high *MI* because it was sure that "Forecast 1" was the sign of "Actual 3". It had got worst *R* which could be an important index to evaluate forecasts in this situation.

The fourth data set (Table 2d) was an example of a spuriously good forecast. This forecast had got highest *HR*, but was clearly inefficient because *H*(*A*) was naught. If the current situation was defined as

$$\begin{cases} Forecast\ 1 = \{Catch \mid Catch < 1\} \\ Forecast\ 2 = \{Catch \mid 1 \le Catch \le 1000000000\} \\ Forecast\ 3 = \{Catch \mid 1000000000 < Catch\} \end{cases} \tag{8}$$

there was no room for failure. In the current situation, if a forecaster continued to predict "Forecast 2", *HR* becomes 100%. However, this forecast lacked information and *MI* was naught.

Fishing forecast

In the current study, Pacific saury fishing forecasts were evaluated as an application. The Pacific saury fishing forecast is essential information for the saury fisheries industry in Japan, and has been conducted for more than 50 years [18]. Since the unit price of Pacific saury is unstable corresponding mainly to the daily catch in the

landing port, it is important to forecast the fish abundance to prevent an excessive catch and to stabilize the unit price[7].

In the current study, three types of Pacific saury fishing forecasts were used. The first was a change-ratio forecast for a short period, and was abbreviated as “(a) short-term change-ratio forecast”. A change-ratio forecast only predicted the change in catch, but not the amount of the actual catch. The second was “(b) short-term level forecast”. A level forecast predicted the amount of fish caught. Both the (a) short-term change-ratio and (b) short-term level forecasts were provided by Tohoku National Fisheries Research Institute (TNFRI) and Japan Fisheries Information Service Centre (JAFIC). Short-term forecasts predicted the fishing conditions in the East Hokkaido area, Sanriku area, and Joban area. The current study used the ten-day forecasts off East Hokkaido from 2002–2009, because of the richness of the data sets. Short-term forecasts were determined by the consensus of researchers through a comprehensive review of the results of several numerical models [19].

In the forecast contents, "prospects", "outline of forecast", "overview of fishing condition" were described. In the current study, "outline of forecast" was used as the forecast result. Level or change ratio of the actual catch was defined by the "overview of fishing condition", and was used for the evaluation. The forecast in 2002 and 2003 were omitted, because the content did not include the description of conditions, and the forecasts cannot be evaluated. Since the level or change ratio of the forecast and/or actual catch cannot be determined from the content, some forecasts in 2004–2009 were omitted (Table S1). Consequently, sample sizes of (a) short-term change-ratio and (b) short-term level forecasts were different (n=34 and 33, respectively).

The third type was the long-term fishing forecast for Pacific saury in the north western Pacific Ocean for 1972–2009. The forecast results for 1972–87 were from a list of fishing forecasts [9], whereas the results for 1988–2009 were from the annual report of the research meeting on saury stock (1990–2011) [20-22]. Since this type of forecast only contained the yearly change ratio, it was abbreviated as "(c) long-term change-ratio forecast". The current study used the long-term change-ratio forecasts published in August. The long-term change-ratio forecast predicts the fishing conditions from August to December. This forecast was created by compiling the results of the study conducted by TNFRI and other institutions. The forecast method was not explicitly described. In particular, this forecast was decided not by statistical modelling but by consensus. Even in these situations, the indices used in the current study can be calculated.

The actual fisheries conditions were determined using the fish abundance index, which was the accumulation of the mean catch per haul for a 30-minute grid over a ten-day period [22]. Due to the lack of actual fisheries conditions data in 1996, the forecasts were evaluated only for 1972–1995 and 1998–2009 (n=36). Following to the Hokkaido Research Organization, Central Fisheries Research Institute (HRO, Central Fisheries Research Institute: http://www.fishexp.hro.or.jp/exp/central/kanri/SigenHyoka/index.asp, "accessed 13 December 2013".), three options (increasing, stable, decreasing) were defined from the change ratio of abundance index CR_j as

$$CR_j = \frac{\left|Y_{j+1} - Y_j\right|}{Y_j} \tag{9}$$

where Y_j was the actual fish abundance index in year j. $\overline{CR}_j$ was calculated as

$$\overline{CR}_j = \begin{cases} \frac{1}{20}\sum_{l=1972}^{1991} CR_l \text{ for } j = 1972,...,1991 \\ \frac{1}{20}\sum_{l=j-20}^{j-1} CR_l \text{ for } j = 1992,...,2009 \end{cases} \quad (10)$$

Due to the lack of datasets, the mean abundance indices of 1972-1991 were used in substitution for actual past fishing condition before 1991. The options were defined based on the following criteria:

$$\begin{aligned} &\text{increasing}: && CR_j > k\overline{CR}_j \text{ and } Y_{j+1} > Y_j \\ &\text{stable}: && CR_j \le k\overline{CR}_j \\ &\text{decreasing}: && CR_j > k\overline{CR}_j \text{ and } Y_{j+1} < Y_j \end{aligned} \quad (11)$$

Parameter k was set to 0.4 which was equivalent to the verification result in the annual report of the research meeting on saury resource such as the "fishing condition was same as forecasted result" and "fishing condition was different from the forecast results" [23-29]. All of the verification results in the current study consisted with past verification results, except for the option in 2008 [28].

In the long-term fishing forecast, some forecasts (see Table S2) were level forecasts instead of change-ratio forecasts and level forecasts were transformed into change-ratio forecasts. The fishing condition level was also defined according to HRO, Central Fisheries Research Institute (HRO, Central Fisheries Research Institute: http://www.fishexp.hro.or.jp/exp/central/kanri/SigenHyoka/index.asp, "accessed 13 December 2013".) as

$$\begin{aligned} &\text{large}: && \frac{Y_j}{\overline{Y}_j} - 1 > k \\ &\text{medium}: && \left|\frac{Y_j}{\overline{Y}_j} - 1\right| \le k \\ &\text{small}: && \frac{Y_j}{\overline{Y}_j} - 1 < -k \end{aligned} \quad (12)$$

where

$$\overline{Y}_j = \begin{cases} \frac{1}{20}\sum_{l=1972}^{1991} Y_l \text{ for } j = 1972,...,1991 \\ \frac{1}{20}\sum_{l=j-20}^{j-1} Y_l \text{ for } j = 1992,...,2009 \end{cases} \quad (13)$$

Parameter k was also set to 0.4, which was the default value of HRO, Central Fisheries Research Institute (HRO, Central Fisheries Research Institute: http://www.fishexp.hro.or.jp/exp/central/kanri/SigenHyoka/index.asp, "accessed 13 December 2013".). If actual condition in the previous year was "low level" and forecast in next year was "forecast medium" or "forecast large", the forecast were transformed "forecast increase", and vice versa. The current definition was different from equation (11) because of the lack of quantitative criterion for transformation.

The fishing condition was divided into three options: "(1) large", "(2) medium", and "(3) small" or "(1) increasing", "(2) stable", and "(3) decreasing". To evaluate each forecast, the probability distributions of forecasts (Table 1) were created by normalizing the contingency table, whose total value equals one.

Results

Table 4 shows the probability distributions of the actual fishing conditions and the fishing forecasts for the (a) short-term change ratio, (b) short-term level, and (c) long-term change ratio. In the (b) short-term level forecast (Table 4b), the forecast marginal probability was exactly the same for the three options (one third for increasing, stable, and decreasing). However, in (a) short-term change ratio and (c) long-term change-ratio forecasts (Tables 4a, c), "forecast decreasing" was much frequently appeared than the other two options.

Table 5 shows the results of the three forecasts evaluations according to the information indices $H(A)$, $H(A|F)$, MI, and R as well as accuracy index HR. The order of HR was: (a) short-term change ratio > (c) long-term change ratio ≈ (b) short-term level. Since $H(A)$ was fairly close among them, the variance in MI was mainly due to that of $H(A|F)$. The order of MI was: (a) short-term change ratio > (b) short-term level > (c) long-term change ratio. The worst R value was appeared in (c) long-term change-ratio forecast, indicating that the (c) long-term change-ratio forecast had got the largest gap between the probability distributions of the forecasted and actual fishing conditions.

Discussion

The order of *HR*, *MI* and *R* sometimes differed for the three types of forecasts. The (a) short-term change ratio had got the highest value in both *HR* and *MI* but was not the best in *R*. Comparing to the (b) short-term level forecast and the (c) long-term change-ratio forecast, the (b) short-term level forecast was worse in *HR* but better in *MI*. The (b) short-term level was best in *R*, worst in *HR* but was fair predictable measured by *MI*.

To investigate the impact of the excess of "forecast decreasing", Table 6 shows the information entropy $H(A|f_i)$ and marginal probability $P(f_i)$ for each option. $H(A|f_i)$ represented the uncertainty of the actual fishing condition for each option (i.e., such as "forecast increasing/large", "forecast stable/medium", and "forecast decreasing/small"). For the (a) short-term change-ratio forecast, $H(A|f_i)$ were relatively small (less than one) regardless of the forecast option. Although "forecast decreasing" was frequently forecasted as $P(f_i) = 0.529$, the overall uncertainty for a given forecast $H(A|F)$ was as small as 0.869 because $H(A|f_i)$ was as small as 0.764. *R* was small and less than half of the (c) long-term change-ratio forecast. Therefore, "forecast decreasing" in the (a) short-term change-ratio forecast was not excessive, despite of the frequent posting of "forecast decreasing". In the (b) short-term level forecast, although $H(A|f_i)$ for "forecast medium" was high, $P(f_i)$ for each forecasted option (large, medium, and small) was balanced, which leaded a moderate overall uncertainty of 1.242 (Table 6). *R* was quite small as 0.027 which indicated that small bias were there. In the (c) long-term change-ratio forecast, $H(A|F)$, was the highest, because $H(A|f_i)$ of "forecast decreasing" was high and too often posted. *R* was worst (0.139) because it posted "forecast decreasing" in excess. Consequently, reducing the frequency bias of

250 “forecast decreasing” will improve the forecast performance.

251 Since 2001, mid-water trawling survey had been conducted prior to the fishing season, and the
252 amount of data available for the forecast had been increased [22]. Consequently, the accuracy and predictability
253 of the (c) long-term change-ratio forecast had improved. Table 7 shows the probability distribution of the actual
254 fishing conditions and fishing forecasts for the (c) long-term change-ratio forecasts, calculated by dividing the
255 long-term data into two data sets; 1972–2000 and 2001–2009. Table 8 shows the indices calculated from the two
256 data sets as well as one pooled data set. Although the sample size of the 2001–2009 data set was much smaller
257 (n=9), *HR*, *MI*, and *R* all showed drastic improvements, mainly because of the reduction of the bias toward
258 “forecast decreasing”.

259 The current method is applicable for quantitative forecasts. Although the current study only employed
260 three categorical forecasts, such as “low, medium, and high” or “declining, stable, and increasing”, information
261 indices can be calculated for a forecast with more categories, as long as the probability distribution can be
262 obtained. For quantitative data, information entropy also can be described, and mutual information can be
263 estimated [30].

264 It would be recommended to use various indices to evaluate comprehensive forecast skill because
265 each index has a limited aspect. If the order of indices is different, forecast characteristic can be described.
266 When, all of the score is good, this is a good forecast (Table 2a). If *HR* is low but *MI* is high, this forecast could
267 be perversity forecast (Table 2c). Conversely, when *HR* is high but *MI* is low, this forecast may predict obvious
268 situations (Table 2d). If only *R* is good and other indices are low, the forecast would hardly provide benefit for

fishers. However, if only R is bad, the forecast would be perverse, such as "forecast increase" indicating "actual decrease" (Table 2c). Even if comprehensive forecast skill can not be defined clearly, predictability may add new viewpoint to evaluation using only accuracy.

One of the advantages of the current method is the wide applicability. Since it requires simple information indices with few assumptions, it can be applied as long as the probability distribution can be obtained. It does not require statistical models, and is easily calculated by using simple equations.

The current study addressed the lack of forecast evaluations in previous works, and provided new evaluation indices. Although these indices are not directly applicable to decision-making for the next action, they may assist better decision indirectly by selecting good forecasting system.

From the results herein, the following guidelines were proposed to create a useful forecast procedure. Firstly, it is recommended to calculate $H(A)$ before making a forecast. When $H(A)$ is quite small, it is better to increase the precision of the forecast option, increasing number of forecasting categories. Secondly, it is highly recommended that HR should be monitored in the beginning of the yearly forecast. After a certain years forecasts, the distribution of the actual and forecasted options should be monitored to optimize R. Lastly, $H(A|F)$ and MI should be monitored for evaluating forecast uncertainty and forecast predictability.

Creating a perfect forecast is nearly impossible. However, monitoring various indices of the forecast will help the improvement of forecasting systems in the limited data.

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Table 1 Probability distribution of the fishing forecast and the actual fishing condition

Fishing forecast	Actual fishing condition			$p(F)$
	Actual 1	Actual 2	Actual 3	
Forecast 1	$p(a_1,f_1)$	$p(a_2,f_1)$	$p(a_3,f_1)$	$p(f_1)$
Forecast 2	$p(a_1,f_2)$	$p(a_2,f_2)$	$p(a_3,f_2)$	$p(f_2)$
Forecast 3	$p(a_1,f_3)$	$p(a_2,f_3)$	$p(a_3,f_3)$	$p(f_3)$
$p(A)$	$p(a_1)$	$p(a_2)$	$p(a_3)$	1

Table 2 Sample data sets of the probability distribution of the fishing forecast and the actual fishing condition

(a) Example 1: Good forecast

Fishing forecast	Actual fishing condition			$p(F)$
	Actual 1	Actual 2	Actual 3	
Forecast 1	0.4	0.05	0	0.45
Forecast 2	0.1	0.3	0	0.4
Forecast 3	0	0.05	0.1	0.15
$p(A)$	0.5	0.4	0.1	1

(b) Example 2: Bad forecast

Fishing forecast	Actual fishing condition			$p(F)$
	Actual 1	Actual 2	Actual 3	
Forecast 1	0.1	0.1	0.1	0.3
Forecast 2	0.1	0.2	0	0.3
Forecast 3	0.2	0.1	0.1	0.4
$p(A)$	0.4	0.4	0.2	1

(c) Example 3: Forecast of perversity

Fishing forecast	Actual fishing condition			$p(F)$
	Actual 1	Actual 2	Actual 3	
Forecast 1	0	0	0.1	0.1
Forecast 2	0	0.5	0	0.5
Forecast 3	0.4	0	0	0.4
$p(A)$	0.4	0.5	0.1	1

(d) Example 4: Spurious good forecast

Fishing forecast	Actual fishing condition			$p(F)$
	Actual 1	Actual 2	Actual 3	
Forecast 1	0	0.01	0	0.01
Forecast 2	0	0.98	0	0.98
Forecast 3	0	0.01	0	0.01
$p(A)$	0	1	0	1

Table 3 Result of evaluation of numerical example

	Ex.1	Ex.2	Ex.3	Ex.4
HR	0.800 (2)	0.400 (4)	0.500 (3)	0.980 (1)
$H(A)$	1.361 (2)	1.522 (1)	1.361 (2)	0 (3)
$H(A\|F)$	0.689 (2)	1.351 (3)	0 (1)	0 (1)
MI	0.672 (2)	0.171 (3)	1.361 (1)	0 (4)
R	0.018 (1)	0.132 (3)	0.600 (4)	0.029 (2)

HR: hit ratio, $H(A)$: information entropy of actual fishing condition, $H(A|F)$: conditional entropy, *MI*: mutual information, *R*: relative entropy. Numbers in parentheses denote the ascending order of goodness of the four sample forecasts. *HR*, $H(A)$ and *MI* are descending orders, and $H(A|F)$ and *R* is ascending orders.

Table 4 Probability of the fishing forecast and the actual fishing condition of three types of forecasts

(a) Short-term change-ratio forecast *n*=34

Fishing forecast	Actual fishing condition			Total
	Actual increasing	Actual stable	Actual decreasing	
Forecast increasing	0.206	0.029	0.029	0.265
Forecast stable	0.088	0.118	0	0.206
Forecast decreasing	0.118	0	0.412	0.529
Total	0.412	0.147	0.441	1

(b) Short-term level forecast *n*=33

Fishing forecast	Actual fishing condition			Total
	Actual large	Actual medium	Actual small	
Forecasted large	0.212	0.061	0.061	0.334
Forecasted medium	0.091	0.121	0.121	0.333
Forecasted small	0	0.091	0.242	0.333
Total	0.303	0.273	0.424	1

(c) Long-term change-ratio forecast *n*=36

Fishing forecast	Actual fishing condition			Total
	Actual increasing	Actual stable	Actual decreasing	
Forecast increasing	0.166	0.028	0.028	0.222
Forecast stable	0.083	0.167	0.028	0.278
Forecast decreasing	0.139	0.111	0.250	0.500
Total	0.389	0.306	0.306	1

Table 5 Results of evaluation of three types Pacific saury fishing forecasts

	(a) Short-term change ratio	(b) Short-term level	(c) Long-term change ratio
HR	0.735 (1)	0.576 (3)	0.583 (2)
$H(A)$	1.455 (3)	1.558 (2)	1.575 (1)
$H(A\|F)$	0.869 (1)	1.242 (2)	1.343 (3)
MI	0.586 (1)	0.316 (2)	0.232 (3)
R	0.075 (2)	0.027 (1)	0.139 (3)

HR: hit ratio, $H(A)$: information entropy of actual fishing condition, $H(A|F)$: conditional entropy, *MI*: mutual information, and *R*: relative entropy. Numbers in parentheses denote the ascending order of goodness of the three forecasts. *HR*, $H(A)$ and *MI* are descending orders, $H(A|F)$ and *R* is ascending orders.

Table 6 Information entropy of each option, information indices, and marginal probabilities

	(a) Short-term change ratio		(b) Short-term Level		(c) Long-term change ratio	
	$H(A\|f_i)$	$P(f_i)$	$H(A\|f_i)$	$P(f_i)$	$H(A\|f_i)$	$P(f_i)$
Forecast increasing /large	0.986	0.265	1.309	0.334	1.061	0.222
Forecast stable /medium	0.985	0.206	1.573	0.333	1.295	0.278
Forecast decreasing /small	0.764	0.529	0.845	0.333	1.496	0.500
$H(A\|F)$	0.869 (1)		1.242 (2)		1.343 (3)	
R	0.075 (2)		0.027 (1)		0.139 (3)	

$H(A|f_i)$: information entropy for each change ratio/level. $P(f_i)$: the marginal probability of the forecast for each change ratio/level. $H(A|F)$: the conditional entropy(weighted mean of H). R: relative entropy. Numbers in parentheses denote the ascending order of the three forecasts.

Table 7 Probabilities of the fishing forecast and the actual fishing condition

(a) Long-term change-ratio forecast in 1972-2000, *n*=27

Fishing forecast	Actual fishing condition			Total
	Actual increasing	Actual stable	Actual decreasing	
Forecast increasing	0.112	0.037	0	0.149
Forecast stable	0.074	0.185	0.037	0.296
Forecast decreasing	0.185	0.111	0.259	0.555
Total	0.371	0.333	0.296	1

(b) Long-term change-ratio forecast in 2001-2009, *n*=9

Fishing forecast	Actual fishing condition			Total
	Actual increasing	Actual stable	Actual decreasing	
Forecast increasing	0.333	0	0.111	0.444
Forecast stable	0.111	0.111	0	0.222
Forecast decreasing	0	0.111	0.222	0.333
Total	0.444	0.222	0.333	1

Table 8 Hit ratio (*HR*) and information indices for the long-term change-ratio forecast

	1972-2009	1972-2000	2001-2009
HR	0.583	0.556	0.667
$H(A)$	1.575	1.579	1.530
$H(A\|F)$	1.343	1.342	0.889
MI	0.232	0.237	0.642
R	0.139	0.278	0
n	36	27	9