# A general method to adjust catch limits/targets with survey uncertainty

**Dana Hanselman**

NOAA Fisheries, Alaska Fisheries Science Center, Auke Bay Laboratories, Juneau, AK

## *Abstract*

Recent interest in incorporating uncertainty into how quotas are established for marine resources has brought a myriad of complex procedures. In this study, I show the use of a simple "catch-all" procedure to use survey biomass uncertainty to compute an Acceptable Biological Catch (ABC) or Annual Catch Limit (ACL) that incorporates uncertainty. As opposed to techniques that use model derived uncertainty estimates, this technique is available to nearly all stock and regions (assuming the stock is caught in a survey) and captures both process and measurement error. By using the coefficient of variation of a time series of biomass estimates or a Kalman filter variance estimate, I potentially account for both life history (short-lived stock with rapid fluctuations), and poorly surveyed stock (high variability from sporadic capture). Under current federal budget constraints, important biomass surveys are in jeopardy. Therefore, the uncertainty adjustment is compounded by the length of time since the last survey. This adjustment could also be used to account for the length between assessment updates. To illustrate the technique, the adjustment is applied to a variety of stock across regions.

## *Introduction*

The Magnuson-Stevens Fishery Conservation and Management Act (MSA) was reauthorized and amended on January 12, 2007, by the Magnuson Stevens Fishery Conservation and Management Reauthorization Act (MSRA 2007). The MSRA established new requirements to end and prevent overfishing, including Annual Catch Limits (ACLs) and Accountability Measures (AMs). Specifically in MSA section 303 (a)(15), fishery management plans shall

> "establish a mechanism for specifying annual catch limits in the plan (including a multiyear plan), implementing regulations, or annual specifications, at a level such that overfishing does not occur in the fishery, including measures to ensure accountability."

These annual catch limits are to apply to all fisheries with two exceptions: (1) stock that have a life cycles of one year or less, and (2) fisheries that are provided for under an international agreement in which the U.S. participates (e.g. The International Pacific Halibut Commission). A working group was convened to provide guidance on the application of ACLs for U.S. fisheries (Rosenberg et al. 2007) and a final rule on guidance for the implementation of ACLs was published on Januray 16, 2009 and was enacted on February 17, 2009 (Department of Commerce 2009). Several key guiding principles were:

(1) As a default or starting point, preventing overfishing applies to ALL stocks, therefore, so should ACLs.

(2) To successfully end and prevent overfishing, OFL (Overfishing Level) > ABC (Acceptable Biological Catch) ≥ ACL.

(3) Uncertainty is inevitable and should be accounted for in setting ABC and ACL.

(4) Consideration of risk must include some evaluation of the vulnerability of a stock to the fishery.

One of the difficulties of meeting the first guideline is that across regions and stock, stock assessment scientists apply a wide variety of analytical techniques on a wide variety of data types and quality to determine limits and targets for fishing mortality. Ideally, risk and uncertainty could be estimated directly from data and managers could choose what level of risk-aversion that is appropriate for particular fisheries. Unfortunately, a small proportion of fisheries have sufficient data to estimate reliable probability distributions of key parameters such as female spawning biomass and MSY fishing mortality (e.g. only two stocks in the Alaska region). Therefore, to meet the first guideline, a procedure is needed that works for fisheries that are both data-poor and data-rich.

However, to satisfy the third and fourth guidelines, uncertainties about both the stock size and the vulnerability of a stock to the fishery need to be accommodated for. As stated previously, quantification of these uncertainties is straightforward for data-rich stocks and can be estimated from maximum likelihood or Bayesian models. The majority of stocks do not have the data to produce model-derived estimates of uncertainty, and must rely on simpler methods.

In this study, I show the use of a simple generalized procedure to use survey biomass uncertainty to adjust quotas to make an Acceptable Biological Catch (ABC) that incorporates uncertainty. As opposed to techniques that use model derived uncertainty estimates, this technique is available to nearly all stock and regions (assuming the stock is caught in a survey) and captures both process and measurement error. By using the coefficient of variation (CV) of a time series of biomass estimates or a Kalman filter derived CV, I potentially account for both life history (short-lived stock with rapid fluctuations), and poorly surveyed stock (high variability from sporadic capture). Under current federal budget constraints, important biomass surveys are in jeopardy. Therefore, the uncertainty adjustment is compounded by the length of time since the last survey. Since some regions do not regularly update assessments, this adjustment could also be used to account for the length between assessment updates. To illustrate the technique, the adjustment is applied to a variety of stocks across regions.

## *Methods*

Table 1. Abbreviations and mathematical symbols

| | |
|---|---|
| *ACL* | Annual Catch Limit |
| *ABC* | Acceptable Biological Catch |
| CV | Coefficient of Variation (SD/mean) |
| *OFL* | Overfishing Level |
| $Z^{-1}$ | Inverse-normal function |

## Caddy-McGarvey Extended

Caddy and McGarvey (1996) developed a framework the compute a "target reference point" using simple statistical theory to allow a manager to choose an acceptable probability of exceeding MSY or a "limit reference point". In the Caddy-McGarvey framework (CM), a probability distribution for fishing mortality is assumed and MSY is assumed known exactly. Prager et al. (2003) generalized the CM framework by allowing uncertainty in both estimates of fishing mortality and MSY fishing mortality. While the Prager et al. (2003) method is preferable in situations where an estimate of the precision of MSY is easily obtainable, I prefer an approach that applies to more levels of data availability. In this analysis, I reverse the CM framework to determine a buffer size utilizing uncertainty in the limit reference point based on the uncertainty in a survey biomass index.

The most straightforward way to implement an ABC will be to base it on the way OFLs are already determined, which can be quite different across stock and region. For example, in Alaska fisheries, OFL and ABC can be determined by an age-structured model using Spawners-per-recruit (SPR) proxies for MSY in a relatively data-rich stock. Conversely, OFL and ABC may be determined by multiplying an estimate of natural mortality with a three year average of survey biomass estimates. ABC is computed as 0.75 *x* OFL. While these methods attempt to buffer against uncertainty within the same perceived level of data-richness, uncertainty is not explicitly accounted for between stocks at the same level. For our method, I start with an OFL determined by whatever method the particular Council prescribes for the stock and data-quality. Then, a manager chooses what level of risk is acceptable that the ABC/ACL exceeds the true OFL. Presumably, this level should not exceed 50%, which would mean ABC is set equal to or higher than OFL, a level that is prohibited by the MSRA.

The assumption could be made that the buffer proportion could be either normal or lognormal.

$$\Pr(ABC > OFL) = \int_{p_{next}}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_{p_{next}}} e^{\left[-\frac{(p_{next}-p)^2}{2\sigma^2_{p_{next}}}\right]} dp = P^* \qquad (1)$$

The normal approximation of this integral is

$$ABC = OFL \cdot p_{next} = \frac{OFL}{(1+CV_{p_{next}})Z^{-1}(1-P^*)} \qquad (2)$$

where $CV_{p_{next}}$ is the approximation of survey CV used, $Z^{-1}$ is the inverse normal approximation and $P^*$ is the level of risk assumed by the manager, the probability that the ABC exceeds the actual OFL.

The lognormal approximation is

$$ABC = OFL \cdot p_{next} = \frac{OFL}{e^{\sqrt{\log_e(1+CV^2{}_{p_{next}})}Z^{-1}(1-P^*)}} \qquad (3)$$

Finally, each year following a survey without a new survey, there would be a compounding of the uncertainty buffer based on multiplicative probabilities.

$$ABC_t = OFL \cdot (p_{next})^{\frac{t}{i}} \qquad (4)$$

where $ABC_t$ is the acceptable biological catch in year $t$ from the last survey estimate, and $i$ is an arbitrary constant if it is to desired to assume that the probabilities are not i.i.d. events. I use $i$=2 for the examples in this study. Illustrations of these three different methods for probabilistically determining the catch limit are contrasted in Figure 1.

## Choosing a CV from survey data

Essential to the methods described here is the choice of CV used in the assumed distribution of the ABC buffer size. I contend that using a CV that accounts for not only the uncertainty of the most recent survey, but the inter-survey variability contains information about both the quality of the survey (measurement error) and the biological variability (process error) of the stock. I discuss a number of methods to choose the appropriate CV, and show two methods in our examples that I suggest are the most appropriate.

Several ways to compute a survey biomass CV for use in this method exist:

1) The sampling error CV of the last survey
2) The mean of all survey sampling error CVs
3) The mean of the last several sampling error CVs (e.g. last 3)
4) The CV of the time series of the biomass index

5) The posterior Kalman filter CV of the biomass index time series
6) An assessment model derived CV estimate

Because this is a method to be used across as many possible stock as possible, I will discuss methods 1-5, and only mention 6 to point out that model-based estimates of uncertainty for data-rich stocks could be used in this method instead. There are advantages and disadvantages to each approach. When the sampling error CV of the last survey is used (1), this gives maximum weight to the most recent information and accounts for the distributional aspects of the population and how well it is sampled by the survey, but not temporal changes in the population. When the mean sampling CV of all surveys is used (2), this gives what the "typical" sampling error is for the stock, but does not account for trends in time (e.g. distributional changes). If the mean of the last several sampling error CVs is used (3), this is a compromise between (1) and (2) by giving weight to more recent information, but protecting from using one outlier CV. Computing the CV of the time series of the biomass index utilizes the information of large changes between surveys (4), which can be caused by both sampling error and biological/environmental changes. The CV of the underlying state variable could be computed using a random-walk Kalman filter model (5), which also accounts for process and measurement error, but in a more rigorous way than (4) and is briefly explained below.

## Kalman Filter methods

Here I describe the equations in the calculations for using the Kalman filter method to obtain a posterior CV on the last survey biomass estimate that accounts for process and measurement error. I will only present the specific recursive equations for the univariate Kalman filter approach here. Useful overviews of the Kalman filter are provided by Meinhold and Singpurwalla (1983) and Pella (1993). Schnute (1994) provides general theory of the Kalman filter approach for estimating fisheries models.

### *Observation equation*

$$y_t = b_t + v_t$$

where $y_t$ is an estimate of the unobservable state of nature, which is the sum of $b_t$, the biomass estimate at time $t$ and $v_t$ is the observation error.

### *State equation*

$$b_t = b_{t-1} + w_t$$

where $b_t$ is the sum of the previous biomass estimate and a process error, $w_t$.

It is assumed that $w_t$ and $v_t$ are independent.

### *Prediction equations*

$$\hat{b}_{t|t-1} = \hat{b}_{t-1}$$

where the prior biomass $\hat{b}_{t|t-1}$ in year *t* is equal to the posterior biomass in year *t*-1.

$$P_{t|t-1} = P_{t-1} + \sigma_w^2$$

The prior variance $P_{t|t-1}$ is equal to the posterior variance $P_{t-1}$ in year *t*-1 summed with the process error $\sigma_w^2$.

### *Update equations*

$$F_t = P_{t|t-1} + \sigma_v^2$$

The mean squared error of $\hat{y}_{t|t-1}$, $F_t$ is the sum of the prior variance $P_{t|t-1}$ at time *t*-1 and the observation error $\sigma_v^2$ at time *t*

$$e_t = y_t - \hat{b}_{t|t-1}$$

The error, $e_t$, is the difference from the survey biomass estimate $y_t$ in year *t* from the prior biomass estimate $\hat{b}_{t|t-1}$

$$\hat{b}_t = \hat{b}_{t|t-1} + P_{t|t-1} F_t^{-1} e_t$$

The posterior or Kalman predicted estimate of biomass $\hat{b}_t$ in year *t* is equal to the prior estimate $\hat{b}_{t|t-1}$ summed with the prior variance $P_{t|t-1}$ divided by the mean squared error of $\hat{y}_{t|t-1}$, $F_t$ and multiplied by the prediction error $e^t$.

$$P_t = P_{t|t-1} - P_{t|t-1}^2 F_t^{-1}$$

The posterior or Kalman variance, $P_t$, is the prior variance $P_{t|t-1}$ minus the square of the prior variance, $P_{t|t-1}^2$, divided by the mean squared error of $\hat{y}_{t|t-1}$, $F_t$.

## Choosing a *P** value

The value of *P** chosen should be chosen as a measure of management uncertainty. One way to choose this value would be to make an adjustment to *P** based on past performance of the ABC setting system. Assuming the ABC should not be exceeded more than half of the time, the default value is 0.5. An adjustment based on past performance could be based on the proportion of overages in some number of recent years. A simple formula for *P** would be:

$$P^* = 0.5 - 0.5\frac{o}{t+1} - c \qquad (5)$$

Where $o$ is the number of overages during $t$ past assessment years. One is added to the denominator to insure a $P^*$ of zero does not occur and $c$ is a constant for additional management uncertainty.

## *Results/Examples*

To illustrate the different versions of the method, I apply it to example stocks that vary in life history, region, and data-richness. I compiled example data sets of eight stocks from various sources with their associated survey estimate time series and CVs in Table 1. Some of these stock are surveyed annually, have current surveys, and are considered well sampled. Others have been surveyed in the past, but not synoptically and have no current survey. I believe these methods can be applied to any of these data sets.

While I show the method applied to many stocks, three specific examples were chosen to represent different typical situations. In each stocks time-series graph, I also show the Kalman Filter estimates of the time-series with associated uncertainty.

(1) Current, annual, synoptic surveys – George's Bank Atlantic Cod

(2) Current, biennial/triennial, synoptic survey – Gulf of Alaska arrowtooth flounder

(3) Past, annual, non-synoptic survey – Gulf of Mexico red grouper

### George's Bank Atlantic cod

I use the weight/tow results and associated CVs from the Northeast Fisheries Science Center's autumn bottom trawl survey from 1963-2007. This is an example of a stock that has an annual long-term survey, with good distributional coverage, and has shown large changes in the population size (Figure 2).

### Gulf of Alaska arrowtooth flounder

I use the absolute biomass estimates (tons) and associated CVs from the Alaska Fisheries Science Center's triennial/biennial bottom trawl survey from 1984-2007. This is an example of a stock that has a current, non-annual, medium-term survey with good distributional coverage and low survey CVs (Figure 3).

### Gulf of Mexico red grouper

I use an abundance index from a zero-inflated delta-lognormal model of Southeast Fisheries Science Center's longline survey catches of Gulf of Mexico red grouper from 2000-2005 (Ingram et al. 2005). This is an example of a model-derived abundance index and CV, formed by a short-term survey data set, with changing distributional coverage, and high CVs (Figure 4).

## *Effect of survey uncertainty*

The different methods of calculating the survey uncertainty give variable results depending on which of the five methods are calculated (Table 2). I show the use of $P*$=0.25 because it corresponds with exceeding the OFL in one of every four years. Because the time series are different in terms of inter-annual variability (large changes in abundance), and in terms of sampling variability (large annual sampling CVs), different methods behave differently depending on the stock. In the Gulf of Mexico red grouper stock, the CV of the time series was similar to other methods, while in the GOA arrowtooth stock, this method yielded a CV four times higher. Like the GOA arrowtooth stock, George's Bank cod have experienced large changes in biomass so this method is accounting for potential large changes in population, whether environmentally or anthropogenically driven. The Kalman filter estimates generally had the lowest CVs, this is because the filtering process is recursively utilizing information from the rest of the time series to smooth the measurement error component.

When these methods are applied for the three example stock for an ABC adjustment in the next year (Table 3), the adjustment can be slight (GOA arrowtooth flounder), or substantial (George's Bank cod). For most cases, using the coefficient of variation of the time series of biomass estimates yielded the largest downward adjustment, while the CV of the last Kalman filter estimate yielded the smallest downward adjustment.

## *Effect of P* value*

The choice of $P*$ value has a large effect on the size of the downward adjustment. If management is very risk-adverse and chose to target exceeding the ABC in only one of twenty years, the adjustment would be severe for all three stocks under method 4 (time series CV) (Figure 5). Under method 5 (Kalman filter), the $P*$ makes relatively little difference for arrowtooth flounder but has a much larger effect on red grouper and George's Bank cod. If the simple $P*$ formula (5) presented earlier was used, it could be based on the proportion of recent overages. This would be a way to assign an accountability measure (AM) to this method. Arrowtooth has no catch levels in excess of TAC, and data for the other two examples were unavailable. The following table shows example results of the calculations of $P*$ given the number catches in excess of ABC in the last five years with $c$=0:

| Overages | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| $P*$ | 0.50 | 0.42 | 0.33 | 0.25 | 0.17 | 0.08 |

### *Effect of loss of survey*

Compounding the effects of losing a survey over many years could lead to large adjustments for stocks' where the status is already uncertain (Figure 6). In this figure, I use an independence value (*i*) of 2 in equation (4) to compensate for autocorrelation in the unobserved time series. In this analysis, a short lapse in survey would lead to comparable reductions in ABC, while long lapses would lead to disparate differences based on stock uncertainty.

## Discussion

I have proposed a relatively simple and general approach for deriving an adjustment to a standard catch limit (OFL) to determine a more conservative limit (ABC or ACL) to be exceeded with some set amount of probability. The ideas in this study are not novel, but a variation on prior authors' work (Caddy and McGarvey 1996, and Prager et al. 2003).

However, this study shows an application on how survey uncertainty can be incorporated directly into setting new limits and targets required by the new MSRA guidelines. In its most basic form, the method could be used with variable quantities (*P*, i,* and *c*) set the same across stocks and regions which would promote transparency and standardization.

Conversely, these variables offer some amount of flexibility to account for other uncertainties. The values of *P** and *c* should likely be set to represent management uncertainty, risk aversion, and socioeconomic concerns by bodies such as the Councils. As demonstrated in our example, this value could be set based on past overages in the fishery. This would be an example of an Accountability Measure where the buffer is automatically reduced when limits are exceeded less often.

Stock assessment biologists should set the value of *i* with some measure of autocorrelation in the survey time-series, fishing pressure, and vulnerability of the stock that reflect how important annual surveys should be in determining future uncertainty buffers. Simulation work based on the known data and biology would be useful in evaluating different values for any of these quantities on a stock-specific basis.

This method's greatest advantage is that it can operate within existing management frameworks. It is not a method that sets a hard biomass target, it sets an uncertainty adjustment to the best available scientific judgment as to what Acceptable Biological Catch is for that stock. This adjustment would become smaller, both when the stock is adequately surveyed, and management effectively limits catch.

This method's greatest limitation is that it requires some kind of survey or survey proxy to come up with a defensible CV to apply. Most species that are caught in a fishery are also caught in a survey, but there will always be stocks or species that "slip though the mesh". For these species, there still will need to be some data-poor system to apply an uncertainty buffer. These should likely be not be subject to Annual Catch Limits because information is so tenuous that any number would be quite arbitrary. The MSRA guidelines do allow for Ecosystem Component stocks to be exempt from ACLs and for some stocks, this will be the necessary avenue. Future work in this area should be focused on how to deal with rare or low-catchability stocks.

# Literature Cited

Caddy, J. F., and R. McGarvey. 1996. Targets or limits for management of fisheries? N. Am. J. Fish. Manage. 16:479–487.

Department of Commerce. 2009. Magnuson-Stevens Act Provisions; Annual Catch Limits; National Standard Guidelines. Federal Register 74: 11 (Jan. 16, 2009). 50 CFR Part 600. pp. 3178-3213. http://www.nmfs.noaa.gov/msa2007/docs/acl_final_rule.pdf.

Ingram, G. W., M. Grace, L. Lombardi-Carlson, and T. Henwood. 2005. Catch rates, distribution and size/age composition of red grouper, *Epinephelus morio*, collected during NOAA Fisheries Bottom Longline Surveys from the U.S. Gulf of Mexico. SEDAR 12-DW-5. http://www.sefsc.noaa.gov/sedar/download/S12%20DW05%20longline%20survey.pdf?id=DOCUMENT

Ingram, G. W. 2007. Abundance indices of king mackerel, *Scomberomorus cavalla*, collected during SEAMAP shallow water trawl surveys in the South Atlantic Bight (1989-2006). SEDAR 16-DW-09. http://www.sefsc.noaa.gov/sedar/download/S16_DW_09.pdf?id=DOCUMENT

Limpert, E., W.A. Stahel, and M. Abbt. 2001. Lognormal distributions across the sciences: keys and clues. Bioscience 51:5, 341– 352.

Meinhold, J., and N.D. Singpurwalla. 1983. Understanding the Kalman filter. Am. Statistician 37: 123-7.

MSRA (Magnuson-Stevens Fishery Conservation and Management Reauthorization Act of 2007). 2007. Pub. L. No. 109-479, 120 Stat. 3575. May 2007.

Pella, J.J. 1993. Utility of structural time series models and the Kalman filter for predicting consequences of fishery actions. In Proceedings of the International Symposium on Management Strategies for Exploited Fish Populations. Edited by G. Kruse, D.M. Eggers, R.J. Marasco, C. Pautzke, and T.J. Quinn, II. Alaska Sea Grant College Program Report No. 93-02. University of Alaska, Fairbanks, Alaska. pp. 571–594.

Prager, M. H., C. E. Porch, K. W. Shertzer, and J. F. Caddy. 2003. Targets and limits for management of fisheries: a simple probability-based approach. N. Am. J. Fish. Manage. 23:349–361.

Quinn II, T. J., and R. B. Deriso. 1999. Quantitative Fish Dynamics, 542 p. Oxford Univ. Press, New York, NY.

Rosenberg, A., D. Agnew, E. Babcock, A. Cooper, C. Mogensen, R. O'Boyle, J. Powers, G. Stefánsson, and J. Swasey. 2007. Annual catch limits report from the Lenfest working group. Lenfest Ocean Program and MRAG Americas. 36 pp.

Schirripa, M.J. 2007. Status of the sablefish resource off the continental U.S. Pacific coast in 2007. http://www.pcouncil.org/groundfish/gfsafe1008/Sable07v3_0.pdf

Schnute, 1994. A general framework for developing sequential fisheries models. Can. J. Fish. Aquat. Sci. 51, pp. 1676–1688.

Stewart, We. J. 2007. Updated U.S. English sole stock assessment: Status of the resource in 2007. http://www.pcouncil.org/groundfish/gfsafe1008/2007_English_sole_update_council.pdf

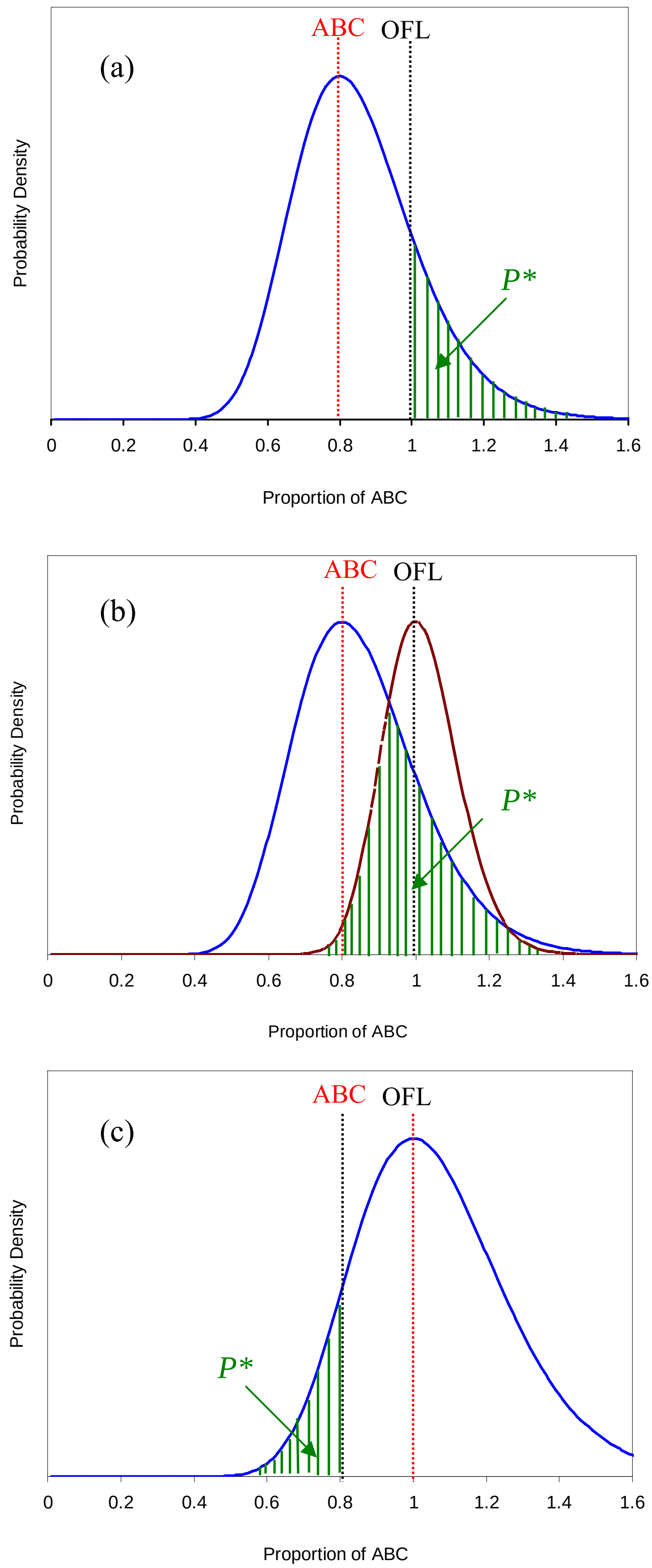


Figure 1. Representations of the interpretation of $P*$ for each of three methods (a) Caddy-McGarvey (1996), (b) Prager et al. (2003), (c) present study. Shaded areas correspond to $P*$.

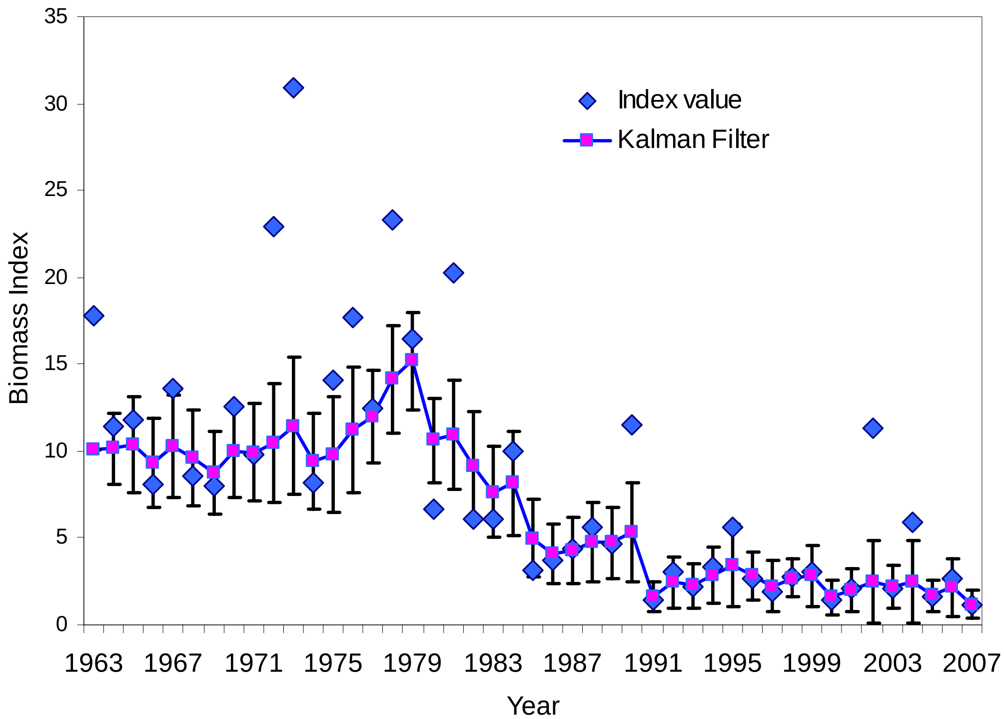


Figure 2. NEFSC autumn trawl survey index of George's Bank Cod (blue diamonds), and Kalman Filter estimates (pink squares with blue line).

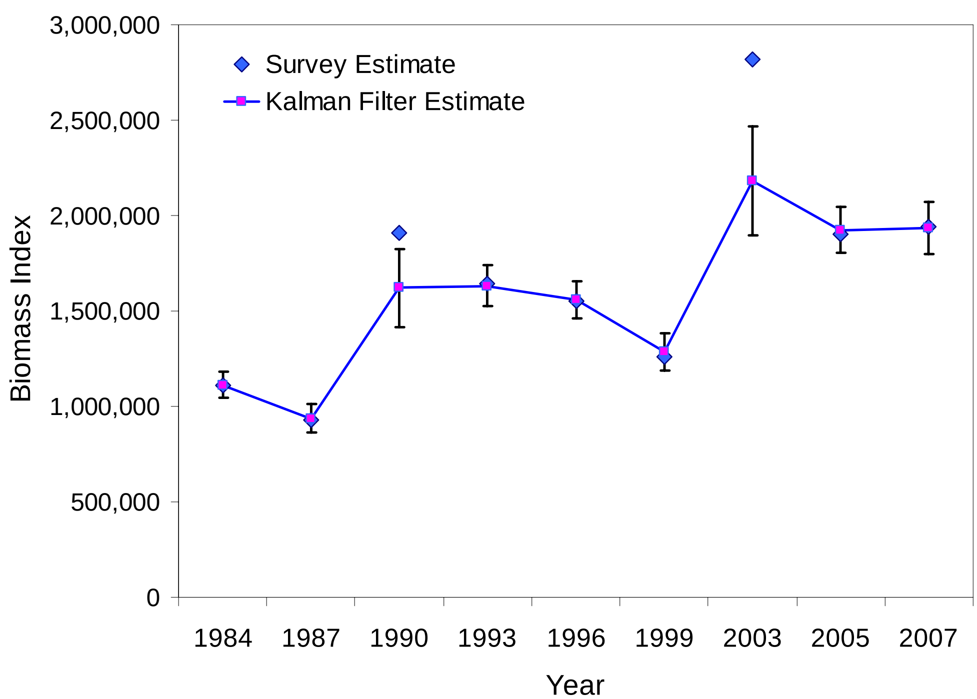


Figure 3. AFSC bottom trawl survey index of Gulf of Alaska arrowtooth flounder (blue diamonds), and Kalman Filter estimates (pink squares with blue line).

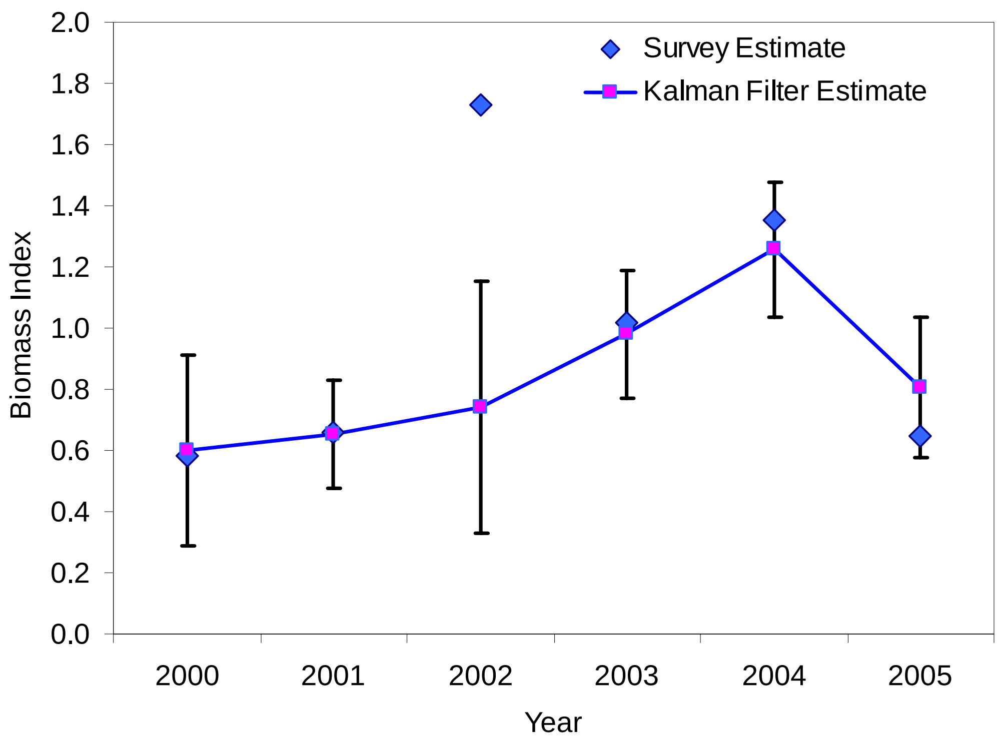


Figure 4. Red snapper (blue diamonds), and Kalman Filter estimates (pink squares with blue line).

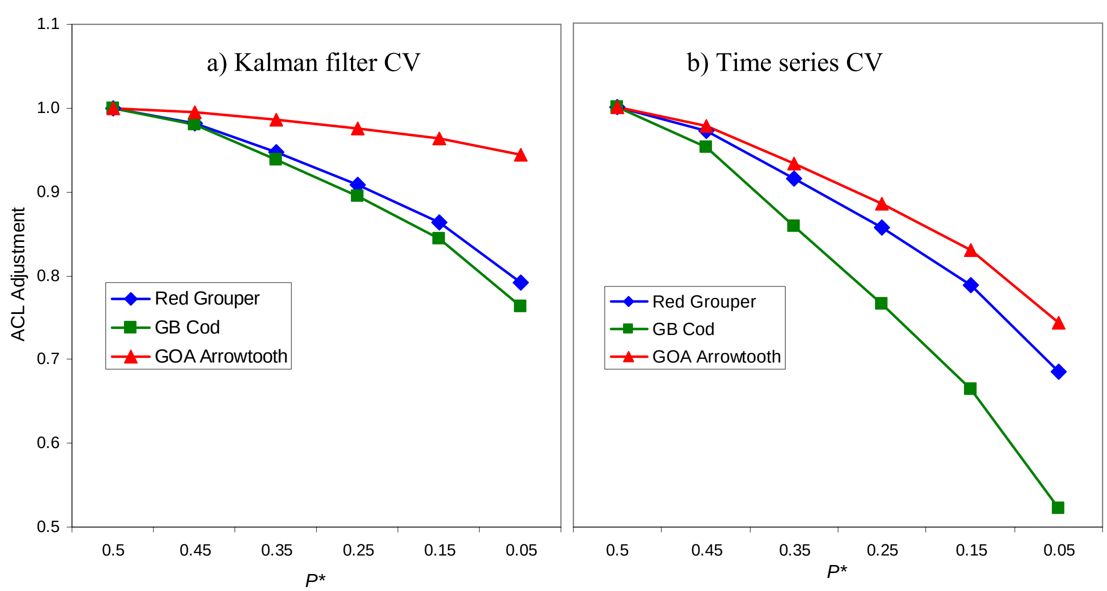


Figure 5. Comparison of different *P** values for two different methods of calculating CVs for use in ACL adjustment.

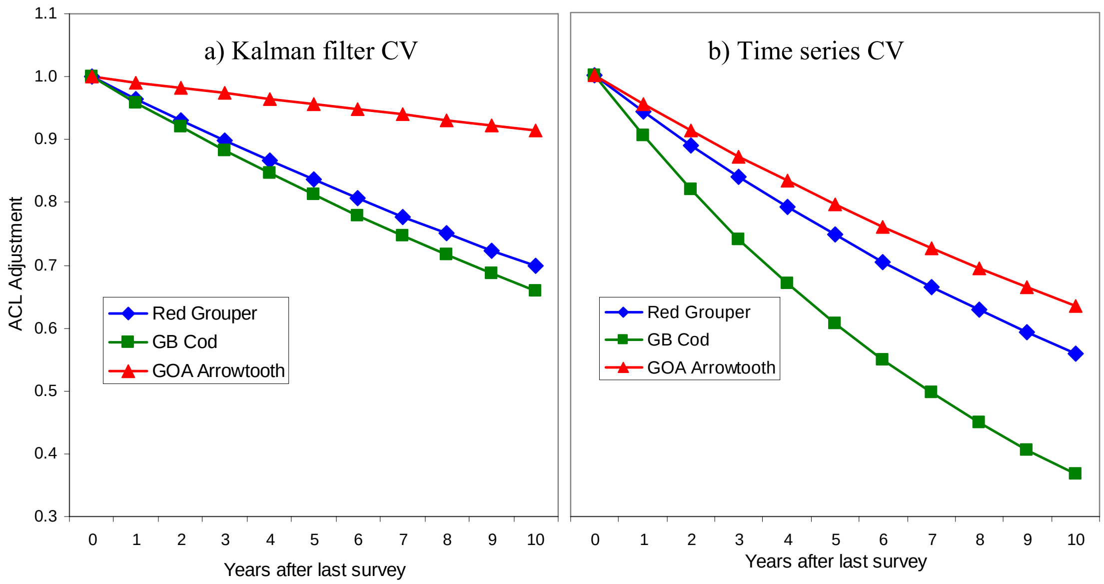


Figure 6. Effect on adjustment to ABC as years without surveys compound. *P**=0.4, *i*=2.

Table 2. Biomass indices and uncertainty (CV, coefficient of variation) for eight stocks.

| | King Mackerel[a] | | Red grouper[b] | | English sole[c] | | WC sablefish[d] | | Acadian redfish[e] | | George's Bank Cod[e] | | GOA Northern rockfish[f] | | GOA Arrowtooth Flounder[f] | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV |
| 1963 | | | | | | | | | | | 17.80 | 0.27 | | | | |
| 1964 | | | | | | | | | 53.6 | 0.75 | 11.40 | 0.30 | | | | |
| 1965 | | | | | | | | | 13.2 | 0.37 | 11.80 | 0.32 | | | | |
| 1966 | | | | | | | | | 29.3 | 0.45 | 8.10 | 0.23 | | | | |
| 1967 | | | | | | | | | 24.4 | 0.37 | 13.60 | 0.23 | | | | |
| 1968 | | | | | | | | | 40.4 | 0.43 | 8.60 | 0.25 | | | | |
| 1969 | | | | | | | | | 23.8 | 0.26 | 8.00 | 0.20 | | | | |
| 1970 | | | | | | | | | 33.0 | 0.19 | 12.60 | 0.19 | | | | |
| 1971 | | | | | | | | | 23.4 | 0.22 | 9.80 | 0.26 | | | | |
| 1972 | | | | | | | | | 24.6 | 0.19 | 22.90 | 0.36 | | | | |
| 1973 | | | | | | | | | 17.0 | 0.18 | 30.90 | 0.29 | | | | |
| 1974 | | | | | | | | | 24.2 | 0.30 | 8.20 | 0.21 | | | | |
| 1975 | | | | | | | | | 40.0 | 0.29 | 14.10 | 0.41 | | | | |
| 1976 | | | | | | | | | 15.3 | 0.39 | 17.70 | 0.24 | | | | |
| 1977 | | | | | | | | | 17.3 | 0.15 | 12.50 | 0.14 | | | | |
| 1978 | | | | | | | | | 20.7 | 0.16 | 23.30 | 0.15 | | | | |
| 1979 | | | | | | | | | 16.0 | 0.21 | 16.50 | 0.13 | | | | |
| 1980 | | | | | 3,544 | 0.17 | | | 12.6 | 0.31 | 6.70 | 0.25 | | | | |
| 1981 | | | | | | | | | 12.2 | 0.32 | 20.30 | 0.44 | | | | |
| 1982 | | | | | | | | | 3.5 | 0.27 | 6.10 | 0.42 | | | | |
| 1983 | | | | | 4,651 | 0.09 | | | 4.1 | 0.23 | 6.10 | 0.30 | | | | |
| 1984 | | | | | | | | | 3.9 | 0.38 | 10.00 | 0.32 | 39,334 | 0.29 | 1,112,215 | 0.07 |
| 1985 | | | | | | | | | 5.7 | 0.31 | 3.10 | 0.46 | | | | |

Table 2. Biomass indices and uncertainty (CV, coefficient of variation) for eight stocks.

| | King Mackerel[a] | | Red grouper[b] | | English sole[c] | | WC sablefish[d] | | Acadian redfish[e] | | George's Bank Cod[e] | | GOA Northern rockfish[f] | | GOA Arrowtooth Flounder[f] | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV | Index | CV |
| 1986 | | | | | 6,254 | 0.09 | | | 8.0 | 0.34 | 3.70 | 0.27 | | | | |
| 1987 | | | | | | | | | 5.5 | 0.32 | 4.40 | 0.30 | 136,417 | 0.29 | 931,598 | 0.08 |
| 1988 | | | | | | | | | 6.3 | 0.57 | 5.60 | 0.34 | | | | |
| 1989 | 0.81 | 0.21 | | | 8,395 | 0.15 | | | 6.8 | 0.30 | 4.70 | 0.29 | | | | |
| 1990 | 2.38 | 0.16 | | | | | | | 12.2 | 0.33 | 11.50 | 0.42 | 107,076 | 0.42 | 1,907,177 | 0.13 |
| 1991 | 0.70 | 0.22 | | | | | | | 8.4 | 0.45 | 1.40 | 0.30 | | | | |
| 1992 | 0.84 | 0.24 | | | 9,510 | 0.10 | | | 8.1 | 0.29 | 3.00 | 0.32 | | | | |
| 1993 | 0.45 | 0.25 | | | | | | | 11.2 | 0.33 | 2.20 | 0.34 | 104,480 | 0.35 | 1,551,657 | 0.06 |
| 1994 | 0.71 | 0.23 | | | | | | | 5.9 | 0.43 | 3.30 | 0.33 | | | | |
| 1995 | 1.23 | 0.20 | | | 5,992 | 0.11 | | | 4.7 | 0.24 | 5.60 | 0.47 | | | | |
| 1996 | 2.26 | 0.17 | | | | | | | 30.6 | 0.33 | 2.70 | 0.28 | 98,965 | 0.27 | 1,639,632 | 0.07 |
| 1997 | 0.52 | 0.24 | | | | | | | 18.9 | 0.39 | 1.90 | 0.48 | | | | |
| 1998 | 1.79 | 0.20 | | | 15,312 | 0.08 | 69,733,110 | 0.23 | 31.7 | 0.45 | 2.80 | 0.21 | | | | |
| 1999 | 1.21 | 0.18 | | | | | 72,400,243 | 0.29 | 22.9 | 0.24 | 3.00 | 0.43 | 242,187 | 0.61 | 1,262,151 | 0.08 |
| 2000 | 0.82 | 0.22 | 0.58 | 0.68 | | | 90,313,581 | 0.23 | 26.2 | 0.29 | 1.40 | 0.37 | | | | |
| 2001 | 0.45 | 0.23 | 0.66 | 0.29 | 12,551 | 0.09 | 74,986,689 | 0.20 | 28.2 | 0.25 | 2.10 | 0.35 | | | | |
| 2002 | 0.51 | 0.21 | 1.73 | 0.83 | | | 66,560,943 | 0.20 | 41.9 | 0.33 | 11.30 | 0.45 | | | | |
| 2003 | 0.99 | 0.20 | 1.02 | 0.22 | | | 87,161,424 | 0.27 | 65.5 | 0.49 | 2.10 | 0.32 | 66,310 | 0.48 | 2,819,095 | 0.13 |
| 2004 | 0.62 | 0.36 | 1.35 | 0.19 | 36,113 | 0.15 | 123,453,322 | 0.34 | | | 5.90 | 0.70 | | | | |
| 2005 | 0.73 | 0.49 | 0.65 | 0.41 | | | 101,271,759 | 0.22 | 47.0 | 0.23 | 1.60 | 0.30 | 359,026 | 0.37 | 1,899,770 | 0.07 |
| 2006 | 1.01 | 0.22 | | | | | 95,970,856 | 0.20 | 50.2 | 0.30 | 2.70 | 0.45 | | | | |
| 2007 | | | | | | | | | 50.4 | 0.25 | 1.10 | 0.37 | 227,069 | 0.38 | 1,939,055 | 0.08 |

Sources: [a] Age-0 king mackerel from SEAMAP SEFSC shall trawl survey, Ingram (2007) p. 8; [b] SEFSC longline survey from Ingram et al. (2005); [c] NWFSC triennial northern bottom trawl survey, Stewart (2007), p.107; [d] NWFSC slope survey, Schirripa (2007), p. 54; [e] NEFSC autumn bottom trawl survey, Legault 2008 (pers. comm., Woods Hole, MA, NEFSC/NMFS); [f] Gulf of Alaska biennial/triennial bottom trawl survey (RACEBASE AFSC/NMFS).

Table 2. Results of using methods 1-5 for calculating CV for use in ABC adjustment for survey uncertainty for eight stocks.

| Method | King Mackerel | **Red grouper** | English sole | WC sablefish | Acadian redfish | **George's Bank Cod** | GOA Northern | **GOA Arrowtooth** |
|---|---|---|---|---|---|---|---|---|
| (1) CV_last | 0.22 | 0.41 | 0.15 | 0.20 | 0.25 | 0.37 | 0.38 | 0.08 |
| (2) CV_mean | 0.24 | 0.44 | 0.12 | 0.24 | 0.32 | 0.32 | 0.38 | 0.09 |
| (3) CV_last 3 | 0.36 | 0.28 | 0.11 | 0.25 | 0.26 | 0.37 | 0.41 | 0.09 |
| (4) CV_all | 0.58 | 0.46 | 0.88 | 0.21 | 0.71 | 0.79 | 0.73 | 0.36 |
| (5) CV_KF | 0.22 | 0.18 | 0.16 | 0.16 | 0.16 | 0.33 | 0.29 | 0.07 |

Table 3. ABC adjustment in 1st year using lognormal method, $P^{*}$=0.25

| Method | King Mackerel | **Red Grouper** | English Sole | WC Sablefish | Acadian redfish | **George's Bank Cod** | GOA Northern | **GOA Arrowtooth** |
|---|---|---|---|---|---|---|---|---|
| (1) CV_last | 0.928 | 0.871 | 0.951 | 0.935 | 0.919 | 0.883 | 0.880 | 0.973 |
| (2) CV_mean | 0.922 | 0.862 | 0.960 | 0.922 | 0.898 | 0.898 | 0.880 | 0.970 |
| (3) CV_last 3 | 0.886 | 0.910 | 0.964 | 0.919 | 0.916 | 0.883 | 0.871 | 0.970 |
| (4) CV_all | 0.822 | 0.856 | 0.743 | 0.932 | 0.787 | 0.766 | 0.782 | 0.886 |
| (5) CV_KF | 0.930 | 0.909 | 0.949 | 0.949 | 0.947 | 0.895 | 0.907 | 0.977 |