

# Effect of forecast skill on management of the Oregon coast coho salmon (*Oncorhynchus kisutch*) fishery

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**Abstract:** Better fisheries management is often given as one justification for research on improving forecasts of fish survival. However, the value gained from expected improvements in forecast skill in terms of achieving management goals is rarely quantified as part of research objectives. Using Monte Carlo simulations of population dynamics, we assessed the effect of forecast skill under two strategies for managing Oregon coast natural (OCN) coho salmon (*Oncorhynchus kisutch*). The first, or status quo, strategy is currently being used to rebuild threatened OCN coho populations. This strategy determines harvest based on both a forecasted marine survival rate and parental spawner abundance. The second strategy relies on a forecast of preharvest adult abundance to achieve a constant spawner escapement target. Performance of the status quo strategy was largely insensitive to forecast skill, while the second strategy showed sensitivity that varied with escapement target and specific performance metric. The results imply that effort towards improving forecasts is not justifiable solely on the basis of improved management under the status quo strategy, though it may be were the management strategy altered.

**Résumé :** Une meilleure gestion des ressources halieutiques est une des raisons communément évoquées pour justifier les recherches sur l'amélioration de la capacité de prévision de la survie du poisson. Cela dit, la quantification de la valeur découlant des améliorations attendues de la capacité de prévision pour ce qui est de l'atteinte des objectifs de gestion est rarement incluse dans les objectifs de recherche. En utilisant des simulations de Monte Carlo de la dynamique des populations, nous avons évalué l'effet de la capacité de prévision dans le contexte de deux stratégies de gestion du saumon coho (*Oncorhynchus kisutch*) naturel de la côte de l'Oregon (OCN). La première stratégie, celle du statu quo, est actuellement utilisée pour reconstituer les populations menacées de saumon coho OCN. Selon cette stratégie, la récolte est établie en fonction des prévisions concernant le taux de survie en mer et l'abondance de géniteurs parentaux. La deuxième stratégie repose sur la prévision de l'abondance des adultes avant la récolte pour en arriver à une cible d'échappée de géniteurs constante. Le rendement de la stratégie du statu quo s'est avéré peu sensible à la capacité de prévision, alors que la sensibilité de la deuxième stratégie variait selon la cible d'échappée et le paramètre de mesure du rendement utilisé. Ces résultats indiquent que l'amélioration de la gestion dans le contexte d'une approche axée sur le statu quo ne justifie pas, à elle seule, les efforts visant l'amélioration des prévisions, mais que ces efforts pourraient être justifiés si la stratégie de gestion était modifiée.

[Traduit par la Rédaction]

## Introduction

Since the late 1800s, Pacific salmon have been a major component of the commercial fishery along the western coast of North America from California to Alaska (Magnuson et al. 1996). However, many salmon populations south of Alaska, including Oregon coast natural (OCN) coho salmon (*Oncorhynchus kisutch*) populations, have seen dramatic declines during the last several decades (Williams et al. 1991; Good et al. 2005). OCN coho adult abundances were estimated to reach as high as 2 000 000 during the first half of the 20th century, but fell below 100 000 in the late 1990s. Concerns over the viability of the Oregon coast coho salmon evolutionarily significant unit, a subset of OCN coho populations, led to their listing as "threatened" in 1998 under the US Endangered Species Act (National Marine Fisheries Service 1998). This status was reconfirmed in 2008 and 2011 (National Marine Fisheries Service 2011).

Since 1995, the Oregon Plan for Salmon and Watersheds (Oregon Plan) has been developed and implemented with the goals of improving freshwater habitat and recovering salmon runs (Oregon Watershed Enhancement Board 2006). An early product of the Oregon Plan was a harvest management strategy for OCN that selected a maximum allowable harvest impact rate (which included both directed and nondirected, or incidental, mortality) based on parental spawner abundances and an expectation of marine survival for a given cohort. This management strategy, based on an exploitation rate matrix, was adopted by the Pacific Fishery Management Council.

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cil in Amendment 13 (A13) to its Salmon Fishery Management Plan (Pacific Fishery Management Council 1998). Furthermore, a review and risk assessment was performed using a detailed habitat-based life-cycle model (Nickelson and Lawson 1998) coupled to a harvest management model to estimate extinction probabilities under the A13 strategy (Pacific Fishery Management Council 2000).

A key feature of the A13 strategy is that the maximum allowable harvest rate for a given year is based in part on a forecast of the marine survival rate; the maximum allowable harvest rate, as a percentage of adults, increases with increasing expected marine survival rate. The accuracy of a forecast thus determines how close the chosen harvest rate is to the “desired” harvest rate (the harvest rate that would be chosen given perfect knowledge of the actual marine survival rate). It follows, therefore, that the forecast accuracy, or skill, impacts how well management objectives are being met under the harvest strategy. The value of an improvement in forecast skill can be quantified by how much closer the improvement brings us to some management objective that would be reached under ideal conditions (i.e., with perfect forecasts).

Walters (1989) found that the value of short-term recruitment forecasts could decline very rapidly as forecast skill decreased and concluded that a forecast method should explain at least 60%–80% of recruitment variation to be of practical use. However, the impact of forecast skill on management performance depended on the specific harvest management strategy; precise forecasts notably improved performance when annual catch quotas were fixed, but not for flexible strategies that adapted in-season to updated stock size estimates. Moreover, for fixed annual catch quotas, the impact of forecast skill was greater when the stock was productive (e.g., salmon) as opposed to being unproductive and long-lived (e.g., Pacific halibut, *Hippoglossus stenolepis*).

Indeed, the importance of accurate forecasts to particular salmon harvest management strategies has been questioned in previous studies. For example, Kaje and Huppert (2007) evaluated the effects of forecast skill on strategies that accounted for both wild and hatchery coho salmon and both offshore and inshore allocation of catch. They found only minor relative gains (on the order of 1%) in terms of total catch for perfect forecasts compared with naïve forecasts of marine survival (i.e., using the long-term mean as the forecast), though gains in total economic value ranged from 2% to 24%, depending on the particular mechanism of how catch was allocated between offshore (more valuable recreational fishing) and inshore (less valuable). Yet smaller relative economic gains (~1.5%) were found by Costello et al. (1998) in perfect over naïve stock abundance forecasts using a bio-economic model of the Pacific Northwest salmon fishery.

Because of the stock- and strategy-dependent conclusions of previous studies, we examined the sensitivity of harvest management strategies for OCN coho to forecast skill. In two separate analyses we looked at (i) sensitivity of the A13 exploitation rate decision strategy to marine survival forecast skill and (ii) sensitivity of constant spawner escapement management strategies to preharvest adult abundance forecast skill. Escapement goal management and various forms of exploitation rate management are the two most common management strategies for Pacific salmon. Although the A13 matrix is more complex than most, conclusions from this

comparison should provide insight into the relative merits of the variety of management systems currently applied to Pacific salmon.

To perform the sensitivity analysis, we applied management strategy evaluation (MSE) methods (e.g., Link and Peterman 1998; Bue et al. 2008; Dorner et al. 2009). Punt et al. (2001) provide a good general overview of the MSE approach. In brief, our MSE method consists of (i) scenario development, (ii) Monte Carlo simulations of population dynamics with harvest strategy implementation, and (iii) strategy evaluation based on performance metrics. Scenarios are defined by the management strategy (i.e., harvest rules), the particular population dynamics model and associated parameter values, and errors in harvest management implementation (e.g., imperfect forecasts; differences between target and actual harvest impact rates).

## Materials and methods

### Data

The OCN coho salmon stock aggregate is defined here as consisting of natural (wild) runs from rivers and lakes along the Oregon coast south of the Columbia River. This stock aggregate is a component of the greater Oregon Production Index (OPI) area coho stock, which also includes hatchery and natural coho from the Columbia River and hatchery coho from the Oregon coast (though coast hatchery coho have historically been a minor component of the OPI and are currently inconsequential because most coastal hatcheries are closed).

An annual time series of aggregated OCN coho preharvest adult recruitment for the period 1970–2009 from Oregon coastal rivers and lakes was generated from spawner escapement estimates and harvest-related mortality (table III-2 in Pacific Fishery Management Council 2010). Data for this period were selected because they were deemed more reliable than earlier estimates because of improvements in surveying methods, which are described in Jacobs and Nickelson (1998) and Lewis et al. (2009). Annual time series of adult recruitment were similarly generated for each of four subaggregate units denoted “Northern”, “North–Central”, “South–Central”, and “Southern”; however, these time series were limited to 1990–2009, the range of the available subaggregate-scale data (Robin Ehlke, Washington Department of Fish and Wildlife, 600 Capitol Way North, Olympia, WA 98501, USA, unpublished data). The geographical extents of the four subaggregate populations are defined in Amendment 13 to the Pacific Coast Salmon Plan (see figure 2 in Pacific Fishery Management Council 1999). Fishery exploitation rates were assumed to be equal across subaggregates.

The OCN coho data set described above does not include estimates of smolt production, which are necessary to determine rates of smolt-to-adult marine survival needed to estimate the parameters in the population models. Therefore, using existing time series of OPI hatchery (OPIH) coho marine survival from 1970 to 2009 as a proxy for OCN coho marine survival, we reconstructed OCN smolt abundance and marine survival time series. Given that marine survival of wild coho has been observed to be higher than that of hatchery coho (Nickelson and Lawson 1998), we adjusted

the OPIH coho marine survival based on wild coho marine survival estimates from a small number of streams along the Oregon coast; details are given in Appendix A. Our interest for this analysis was only in obtaining parameter values that resulted in reasonable approximations of the dynamics of real populations; our primary objective was to examine sensitivity to forecast skill under given management strategies, not to make specific inferences about the OCN coho population.

### Salmon population dynamics

We modeled annual abundance of OCN coho salmon pre-harvest adults  $A$  surviving to their third year as the product of smolt recruitment  $R$  the previous year and a time-varying marine survival rate  $S$ :  $A_t = S_t R_{t-1}$ . After log-transformation, this relationship can be expressed as

$$(1) \quad \ln(A_t) = \ln(R_{t-1}) - M_t$$

where  $t$  is year and  $M$  is a marine instantaneous mortality rate.  $M$  is related to the marine survival rate  $S$  through  $S = \exp(-M)$ , where the time step is implicit. For simplicity, we made no adjustment for early returns of 2-year-old males (jacks) (Koslow et al. 2002; Logerwell et al. 2003). The proportion of coho that return as jacks in this region is estimated to be less than 10% (Suring et al. 2009).

Marine mortality was treated as a stochastic process. Specifically, the marine mortality rate anomaly  $\dot{M}$  (deviation from the mean) was modeled as an autoregressive (AR) process of order  $p$  to capture the autocorrelative properties of marine environmental variables that influence marine survival:

$$(2) \quad \dot{M}_t = \phi_1 \dot{M}_{t-1} + \phi_2 \dot{M}_{t-2} + \dots + \phi_p \dot{M}_{t-p} + \lambda_t$$

where the  $\phi_i$ ,  $i = 1, 2, \dots, p$ , are constants and  $\lambda_t \sim N(0, \sigma_\lambda^2)$ .

Annual recruitment of smolts was modeled with each of two commonly used stock and recruitment models: Ricker (Ricker 1954) and Beverton–Holt (Beverton and Holt 1957). (We also used the hockey-stick model (e.g., Barrowman and Myers 2000), but as results were very similar to those from the Beverton–Holt model, it is not discussed further.) These models can be expressed as

$$(3a) \quad \text{Ricker: } R_{t-1} = \alpha P_{t-3} \exp\left[-\frac{\log(\alpha)}{\beta} P_{t-3}\right] \exp(v_t)$$

$$(3b) \quad \text{Beverton – Holt:}$$

$$R_{t-1} = \alpha P_{t-3} \left(1 + \frac{\alpha - 1}{\beta} P_{t-3}\right)^{-1} \exp(v_t)$$

where  $R_{t-1}$  are the smolt recruits in year  $t - 1$  resulting from parent spawners  $P_{t-3}$  in year  $t - 3$ ,  $v_t$  are the residuals, and  $\alpha$  and  $\beta$  are constants. Though these may not be the most familiar parameterizations of these models, we express them as such so that the parameters have the same meaning across all models. Specifically, when the residual term is zero,  $\alpha$  is the maximum recruits per spawner that occurs as  $P_{t-3} \rightarrow 0$ , and  $\beta$  is the number of spawners at which the number of spawners exactly equals the number of recruits (i.e.,  $R_{t-1} = P_{t-3}$  for  $P_{t-3} > 0$ ).

We considered cross-correlation of the residuals  $v_t$  among the four subaggregate populations. Letting  $v_t$  be a vector of residuals from  $k$  populations, we assumed that the  $v_t$  are nor-

mally distributed with mean zero and variance that is given by the symmetrical covariance matrix  $\Sigma$ :

$$(4) \quad \Sigma = \begin{pmatrix} \sigma_1^2 & C_{12} & \dots & C_{1k} \\ C_{21} & \sigma_2^2 & \dots & C_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ C_{k1} & C_{k2} & \dots & \sigma_k^2 \end{pmatrix}$$

where the  $C_{ij}$  are the covariances of each  $v_i$  and  $v_j$  pair, for  $i \neq j$ .

The recruitment models given by eqs. 3a and 3b could be generalized further to account for autocorrelation of the residuals  $v_t$ . However, we assumed  $v_t$  had no memory, after an exploratory analysis revealed that no significant autocorrelation was found among the residuals  $v_t$  for the aggregate smolt time series, regardless of stock–recruitment model (significance level = 0.05).

We calculated the number of adults that escape the fishery to become parent spawners ( $P$ ) through an annual harvest impact rate  $H$ :

$$(5) \quad P_t = (1 - H_t)A_t$$

The harvest impact rate includes both directed harvest and indirect mortality resulting from harvest practices. For simplicity, we ignored mortality of adults that have escaped harvest impacts (Nickelson and Lawson 1998); mortality rates of freshwater adults due to sport harvest averaged 6% from 1970 to 2009 and averaged only 1% after 1993 (Robin Ehlke, Washington Department of Fish and Wildlife, 600 Capitol Way North, Olympia, WA 98501, USA, unpublished data), while the natural mortality rate in fresh water is considered to be low and relatively constant. Target harvest impact rates were determined from criteria established in a given management strategy. The MSE system also includes a method of calculating error in the implementation of the target harvest impact rate. However, we did not include harvest implementation error in this study so as to isolate the effects of forecast error, though we acknowledge that forecast error could potentially influence harvest implementation error (Holt and Peterman 2006, 2008; Dorner et al. 2009).

To initialize each run, initial parent spawner abundance was set equal to the mean observed spawner abundance during the period 1990–2009, effectively removing initial population size as a source of variability. This meant all results were conditional on initial population sizes being as they have been on average recently, as if we were beginning the experiment in the current “era”. In contrast, we accepted a wide range of initial conditions for marine mortality; prior to each run, we ran the autoregressive model (eq. 2) alone through 100 iterations after first seeding it with mortality anomalies of zero at all lags.

The evaluated management strategies required a forecast of marine survival or annual adult recruitment with a known a priori correlation with the true series. We also desired that the forecast and true series have approximately equal means and variances. To meet these criteria, we generated a forecast by assuming that the forecast  $\hat{X}$  was a linear function of (i) the true variable  $X$ , (ii) the underlying mean  $\bar{X}$ , and (iii) random noise:

$$(6) \quad \hat{X}_t = rX_t + (1-r)\bar{X} + \sqrt{1-r^2}\gamma_t$$

where  $\gamma_t \sim N(0, \sigma_\gamma^2)$ , and  $r$  gives the desired correlation between the forecasted and actual values (Mendenhall and Scheaffer 1973). For marine mortality and adult recruitment,  $X = M$  and  $X = \ln(A)$ , respectively.

### Parameter estimation

The parameters of the AR model for marine mortality (eq. 2) were estimated using the maximum likelihood method with the aggregate population marine mortality estimates for the period 1970–2009. The selection of the order  $p$  of the AR model was based on the Akaike information criterion (AIC); AIC was calculated as  $2(p+1) - 2\ln(L)$ , where  $L$  is the maximized value of the likelihood function (Shumway and Stoffer 2006). The order that provided the lowest  $\Delta\text{AIC}$ , where  $\Delta\text{AIC}(p) = \text{AIC}(p) - \min(\text{AIC})$ , was  $p = 2$ . As a comparison,  $\Delta\text{AIC}$  for  $p = 0, 1, 2,$  and  $3$  were 25.0, 9.4, 0, and 1.8, respectively. Values for the parameters in the marine survival model are provided (Table 1).

The stock–recruitment models (eqs. 3a and 3b) were fitted to the 1990–2009 subaggregate population data using maximum likelihood methods. To facilitate optimization, eqs. 3a and 3b were log-transformed and reparameterized so that the fitting parameters became  $a$  and  $b$ , where  $a = \ln(\alpha)$ , and  $b$  varied by model as follows:

$$(7a) \quad \text{Ricker: } b = \ln(\alpha)/\beta$$

$$(7b) \quad \text{Beverton – Holt: } b = \ln[\beta/(\alpha - 1)]$$

For each model, we chose to keep the value of the parameter  $a$  the same across subaggregates, whereas  $b$  was allowed to vary by subaggregate. This decision was based on a “meta-analysis” that considered all subaggregates simultaneously. Such meta-analyses are based on the concept that ecological parameters shared among nearby populations within a stock ought to be related and that fitting models independently to individual populations is not justified (e.g., Myers et al. 2001; Barrowman et al. 2003). The meta-analysis was performed using mixed-effects models that treat a parameter as coming from a normal distribution (i.e.,  $a_i \sim N(\bar{a}, \sigma_a^2)$  and  $b_i \sim N(\bar{b}, \sigma_b^2)$ ), where  $i$  indexes the subaggregate population (Myers et al. 1999, 2001; Barrowman et al. 2003). By applying a mixed-effects model, we also had the potential for avoiding spurious parameter values for a given subaggregate because of small sample size (Myers and Mertz 1998). The details of the mixed-effects modeling are not given here, but our results showed that subaggregate variability in the  $a$  parameter was insignificant, suggesting  $a$  could be assumed to be equivalent among populations. This may partly be a result of masking some spatial variability in population dynamics by assuming marine survival was identical across subaggregates when reconstructing the smolt time series (as described in Appendix A). Furthermore, there were not major differences in the estimates for  $b$  whether the  $b_i$  were estimated using a mixed-effects model or treated simply as separate coefficients without the distributional constraint imposed by the mixed-effects model. We therefore chose the latter, simpler option. Values for the parameters of the smolt recruitment models are provided (Tables 2 and 3).

**Table 1.** Marine survival AR(2) model parameter values.

Parameter	Value
$\phi_1$	0.315
$\phi_2$	0.475
$\sigma_\lambda$	0.495
$\bar{M}_{ma}$	2.625

### Parameter sensitivity analysis

To see if our overall conclusions were sensitive to the particular values of the parameters used in the smolt recruitment models, we conducted the MSE using alternative parameter sets. Alternative sets were chosen so that they varied from the optimal set to a degree reflective of the parameter uncertainty. Because of computational burden of running many MSE scenarios, we chose only nine alternative parameter sets (excluding the optimal parameter set) per smolt recruitment model.

First, a large number of parameter sets were randomly generated from a multivariate normal distribution. Each parameter set consisted of five parameters ( $a$  and  $b_i$ , for  $i = 1$  to 4). The means and the variance–covariance matrix of the optimal parameter set were used as the mean and variance of the multivariate normal distribution.

From the large sample of randomly generated parameter sets, a subsample was selected based on the likelihood ratio statistic LR:

$$(8) \quad \text{LR} = -2 \ln(L_{\text{ALT}}/L_0)$$

where  $L_0$  is the likelihood of the optimal model (i.e., with the best-fitting parameters that resulted from the maximum likelihood estimation procedure), and  $L_{\text{ALT}}$  is the likelihood of the model with the parameters fixed (the randomly generated parameter set). LR has an approximate  $\chi^2$  distribution. The degrees of freedom (df) of the LR test is the difference between the number of free parameters between the two models, which was 5 in our case. For each of the models given by eqs. 3a and 3b, we randomly chose nine parameter sets that had an LR that corresponded to a significance level of 0.9 ( $\chi^2 = 1.61$  for  $\text{df} = 5$ ;  $L_{\text{ALT}}/L_0 \approx 0.45$ ). This left us with alternative smolt recruitment curves that could be considered to be not significantly different from the best-fitting curve, but still provided a modest range of parameter values (see Table 2).

### Management strategies

We evaluated four management strategies (see summary in Table 4). The first, which is referred to as the “A13a” strategy, is based on the fishery impact rate decision criteria introduced in Amendment 13 of the Pacific Coast Salmon Plan (Pacific Fishery Management Council 1999) and later revised (Scharr et al. 2000). In the A13a strategy, the target harvest rate ( $H_T$ ) depends on two factors: (i) the number of parent spawners relative to habitat capacity (i.e., the percent “seeding”) and (ii) the expected marine survival rate (i.e., adults per smolt) of the forthcoming adult recruits. Furthermore, it is the “weakest” subaggregate stock (the subaggregate stock with the lowest number of parent spawners relative to habitat capacity) that determines the harvest rate in a given year.

**Table 2.** Values of fitted model parameters and range (in parentheses) of the nine alternate parameter values by model and OCN coho sub-aggregate.

Model	Parameter				
	$\alpha$	$\beta$			
		Northern	North-Central	South-Central	Southern
Ricker	65.9 (59.2–74.5)	100.1 (100.1–125.8)	158.4 (139.2–209.1)	272.4 (234.0–324.1)	27.8 (25.7–31.4)
Beverton–Holt	250.3 (160.0–389.0)	390.5 (323.0–522.1)	590.8 (509.9–721.0)	1522.3 (1241.0–1864.6)	118.0 (94.2–141.9)

**Table 3.** Correlation matrix of optimized model residuals for subaggregate populations and total (aggregate) population.

	Northern	North-Central	South-Central
<b>Ricker</b>			
North-Central	0.40		
South-Central	0.23	0.46	
Southern	-0.25	-0.04	0.10
<b>Beverton–Holt</b>			
North-Central	0.56		
South-Central	0.04	0.44	
Southern	-0.26	-0.18	0.11

The harvest impact rate is given as a bivariate step function of the forecast marine survival index and the observed parent spawner status of the subaggregate population with the weakest, or lowest, status (Table 5). Note that the harvest impact rate in each cell of the matrix is given as an upper limit (Table 5). For the Monte Carlo simulations, the upper limit was always applied.

As of 2010, the PFMC was utilizing Columbia River hatchery coho jacks per smolt as an index for adult marine survival. For our study, we used the ratio of adults per smolt directly. The class divisions of the marine survival  $S$  used in our study were taken from appendix 2 of the Oregon Coast Coho Conservation Plan (Oregon Department of Fish and Wildlife 2007) and are as follows: Extremely Low:  $0 \leq S < 0.011$ ; Low:  $0.011 \leq S < 0.044$ ; Medium:  $0.044 \leq S < 0.103$ ; and High:  $0.103 \leq S$ .

The parent spawner status is determined from the percentage of full seeding of high-quality habitat or from the number of spawners per mile (1 mile = 1.609 km) of high-quality habitat. Full seeding is defined as all high-quality habitat being exploited to full capacity. The numbers of spawners required to achieve certain degrees of seeding and a critical number of fish per mile are provided (Table 6).

The second management strategy (A13b) was identical to the A13a strategy except that we doubled all the target harvest impact rates given (Table 5). The third and fourth management strategies applied constant escapement goals of 50 000 and 200 000 total spawners, respectively. These strategies were denoted as CE50 and CE200. The goal of 50 000 spawners was selected because it represented roughly the average annual escapement abundance during the last 30 years of the 20th century (Fig. 1), whereas the goal of 200 000 spawners was chosen as a stock rebuilding strategy. Moreover, the escapement target of 200 000 spawners had been a long-term goal since at least 1981, and this goal was reiterated in the Pacific Coast Salmon Plan (Pacific Fishery Management Council 1997; see also review in Pacific Fishery

**Table 4.** Management strategies.

Strategy	Description
A13a	Current A13 management strategy (status quo)
A13b	A13a with doubled harvest impact rates
CE50	Constant escapement at 50 000 spawners
CE200	Constant escapement at 200 000 spawners

Management Council 1999). Note that with 200 000 spawners, directed harvest would only have occurred in 4 years during the period 1980–2009 (Fig. 1).

For the constant escapement strategies, the target harvest impact rates  $H_T$  were calculated to achieve the target harvest from forecasted adult abundance  $\hat{A}$ :

$$(9) \quad H_t = \begin{cases} 1 - P_T/\hat{A}_t & \text{for } \hat{A}_t > P_T \\ 0 & \text{for } \hat{A}_t \leq P_T \end{cases}$$

where  $P_T$  is the constant target spawner escapement abundance.

### Strategy evaluation

Each scenario was defined by (i) a management strategy, (ii) a specified forecast skill, and (iii) a smolt recruitment model, including a particular parameter set. Sixty years of population dynamics and harvest impacts were simulated for each scenario, which corresponded to tracking three cohorts during nineteen 3-year lifecycles per cohort. 500 trials of the 60-year-long simulations were made per scenario.

Performance metrics were calculated to evaluate the two primary management objectives: (i) economic return and (ii) conservation. For simplicity, we used annual harvest as an index of economic return, avoiding the issue of variable pricing and costs. Specifically, we calculated the mean and 10th and 90th percentiles of annual harvest. These percentiles provide the market with an estimate of the lowest and highest annual harvest that could be expected every 10 years, on average.

To measure the performance of the management strategy in terms of conservation, we tracked the frequency with which subaggregate spawner densities fell below critical seeding levels. The critical seeding threshold (Table 6) represents the spawner density below which demographic risks (i.e., depensation) could become significant (Scharr et al. 2000; Wainwright et al. 2008).

We ran simulations with four levels of forecast skill: Perfect, Good, Fair, and Poor. The corresponding values of the Pearson's correlation coefficient  $r$  as applied to eq. 6 for these skill levels were 1, 0.9, 0.75, and 0.5, respectively. While the goal was to achieve a specific correlation ( $r$ ) between forecasted and actual values to represent a given fore-

**Table 5.** Harvest impact rate decision matrix for strategy A13a.

Parent spawner status <sup>a</sup>	Marine survival index (adult returns per smolt)			
	Extremely Low (<0.011)	Low (0.011 to 0.044)	Medium (0.044 to 0.103)	High (≥0.103)
High: >75% of full seeding	≤8%	≤15%	≤30%	≤45%
Medium: >50% and ≤75% of full seeding	≤8%	≤15%	≤20%	≤38%
Low: >19% and ≤50% of full seeding	≤8%	≤15%	≤15%	≤25%
Very Low: >4 fish per mile and ≤19% of full seeding	≤8%	≤11%	≤11%	≤11%
Critical <sup>b</sup> : ≤4 fish per mile	≤8%	≤8%	≤8%	≤8%

**Note:** The table gives the maximum allowed harvest rate based on parental spawner habitat seeding level (see Table 6) and forecasted marine survival. 1 mile = 1.609 km.

<sup>a</sup>Parental spawner abundance status for aggregate population assumes the status of the weakest subaggregate.

<sup>b</sup>Critical criterion for the Southern subaggregate is ≤12% of full seeding.

**Table 6.** Subaggregate and basin-specific spawner criteria data for strategy A13a.

Subaggregate	Miles of available spawning habitat <sup>a</sup>	100% of full	Critical		Very Low, Low, Medium, and High		
			4 fish per mile	12% of full seeding	19% of full seeding	50% of full seeding	75% of full seeding
Northern	899	21 700	3 596	NA	4 123	10 850	16 275
North–Central	1 163	55 000	4 652	NA	10 450	27 500	41 250
South–Central	1 685	50 000	6 740	NA	9 500	25 000	37 500
Southern	450	5 400	NA	648	1 026	2 700	4 050
Coast-wide total	4 197	132 100	15 636		25 099	66 050	99 075

**Note:** 1 mile = 1.609 km.

<sup>a</sup>Spawning habitat assumes that defined as high-quality habitat only.

cast skill level, specifying the value of  $r$  in eq. 6 did not guarantee each individual 60-year run would return precisely the same value of  $r$  for the simulated time series.

To test for a “detectable” change in a given performance metric due to diminishing forecast skill relative to Perfect skill, we relied on the variability in the performance metrics arising from using the two smolt recruitment models and the 10 parameter sets per model (20 cases in all per forecast skill). Specifically, an increase or decrease in the metric was considered “detectable” if all cases showed an increase or decrease in the metric. Note that the variability of the performance measures among the 10 different parameter sets for a given model was due not only to the varying parameter values, but also included random variability arising from a finite number of Monte Carlo runs. For our purposes, we did not separate the two sources of variability.

Given that the correlation coefficient does not measure the accuracy of the “raw” forecast, but of the forecast under a linear transformation, we also calculated the forecast skill of each 60-year simulation using two additional metrics: the bias and the Nash–Sutcliffe efficiency (NS) (Nash and Sutcliffe 1970). We present the detransformed forecast bias (BIAS) as a percentage:

$$(10) \quad \text{BIAS} = 100 \left[ \exp \left( \frac{1}{n} \sum_{i=1}^n \hat{X}_i - \bar{X} \right) - 1 \right]$$

This way, a BIAS of +10% would indicate, for example, that forecasted survival  $\hat{S} = \exp(\hat{X})$  is, on average, 10% higher than the actual marine survival, which we find easier to interpret than the straight bias of the log-transformed values.

A more comprehensive measure of accuracy is the NS efficiency, with can be shown to be an additive combination of the linear correlation, bias, and the ratio of the variances of forecasted and observed values (Gupta et al. 2009). The NS score is calculated by

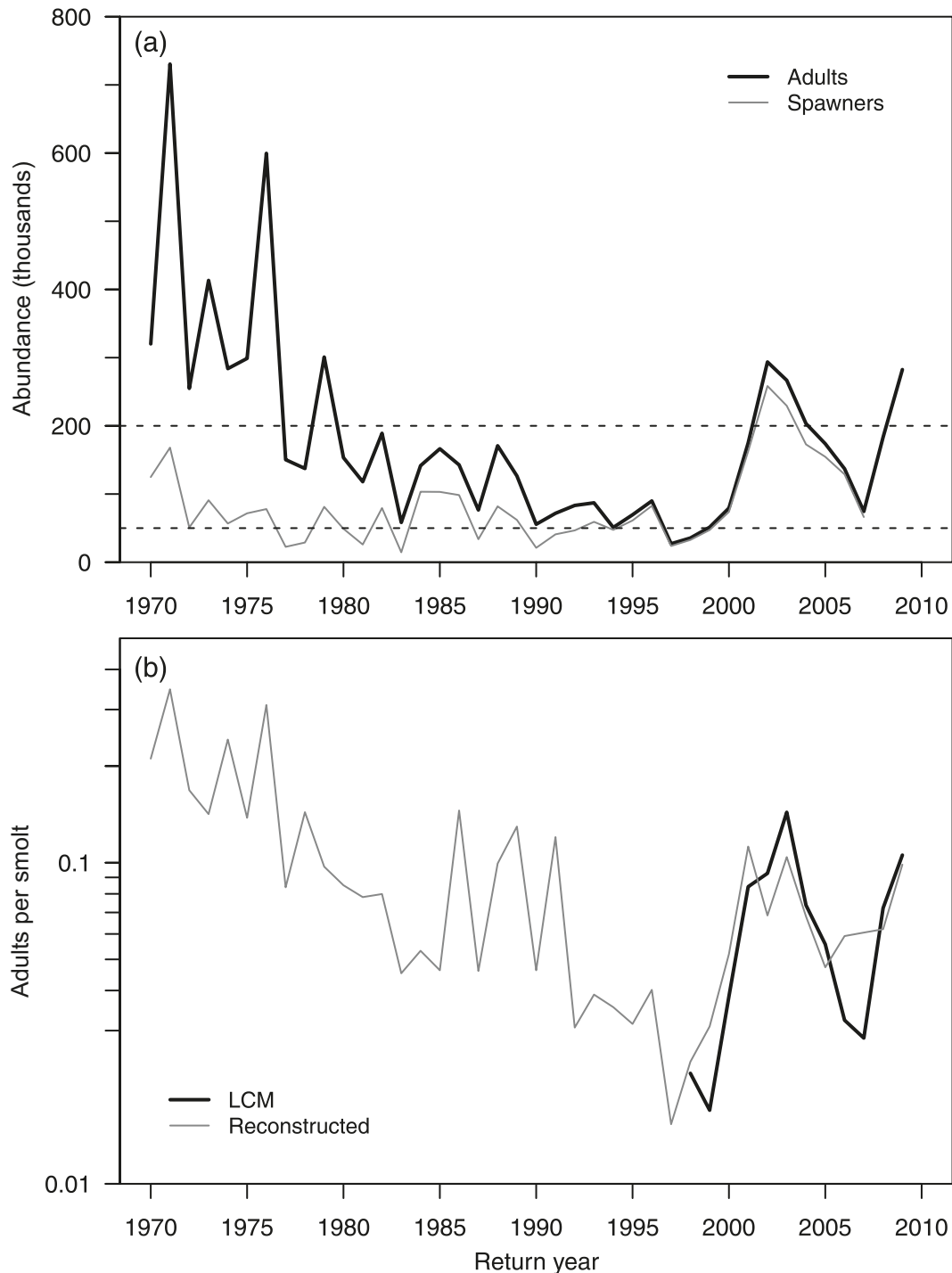
$$(11) \quad \text{NS} = 1 - \frac{\sum_{i=1}^n (\hat{X}_i - X_i)^2}{\sum_{i=1}^n (\bar{X} - X_i)^2}$$

The data estimation and MSE simulations were coded and run using the R language (version 2.10.1; R Development Core Team 2011). The code is available from D.E. Rupp.

## Results

Illustrations of the variability in the correlation  $r$ , the NS efficiency, and bias at different skill levels are shown (Fig. 2). In these examples, the A13a management strategy and the Beverton–Holt smolt recruitment were employed, but the plots looked very similar for all the scenarios (results not shown). Overall, the NS scores were approximately 0.78, 0.45, and –0.11 for  $r = 0.9$ , 0.75, and 0.5, respectively (Fig. 2b). There was an increasing mean bias in the forecast with diminishing forecast skill, but the bias was slight: approximately +0.8%, +1.2%, and +2.6% for Good, Fair, and Poor forecast skill, respectively (Fig. 2c). The variability in bias also increased with diminishing forecast skill. At most, the bias in 9 out of 10 runs varied between –17% and +29% with Poor forecast skill. In the following sections, skill is expressed solely in terms of  $r$ ,

**Fig. 1.** Time series of (a) Oregon coast natural coho adult recruit and spawner abundance and (b) reconstructed marine survival and marine survival estimates from the life cycle monitoring (LCM) sites. Horizontal dashed lines in panel (a) show the target spawner abundances for two management strategies evaluated in this study.

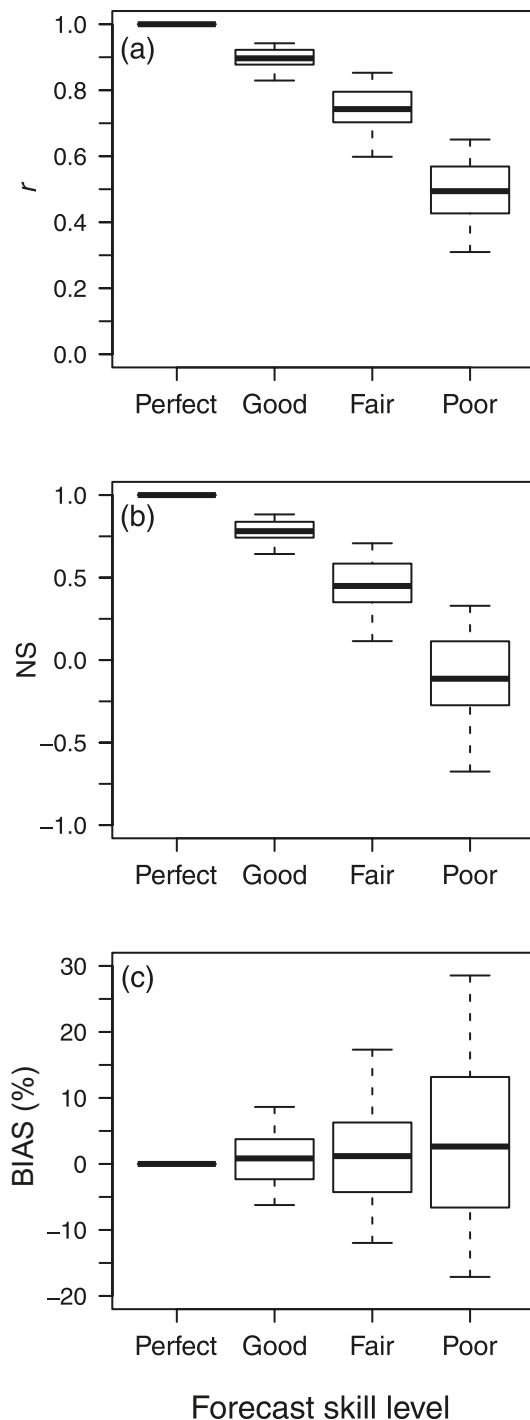


but the above relationships between  $r$  and NS and between  $r$  and BIAS can be assumed throughout with reasonable accuracy.

The effects of diminishing forecasting skill differed greatly by management strategy and by metric. Under the A13a and A13b strategies, changes in mean annual harvest ranged from undetectable to, at most, minor reduction ( $\sim 7\%$ ) (Figs. 3a, 3b). This was true irrespective of the smolt recruitment

model used. Compared with the A13 strategies, however, the constant escapement strategies were more sensitive to forecast skill. For the 50 000 spawner goal, decreases in mean annual harvest at Poor forecast skill were about 15% (Fig. 3c), averaging across smolt recruitment models. Sensitivity of harvest to forecast skill was much higher for the higher spawner abundance target; for 200 000 spawners, the decreases were roughly 15%, 30%, and 45% at the Good, Fair, and Poor

**Fig. 2.** (a) Pearson's correlation coefficient ( $r$ ), (b) Nash–Sutcliffe score (NS), and (c) bias (BIAS) for forecasts by categorical forecast skill level. The bar-and-whisker plots give the mean and 5th, 25th, 75th, and 95th percentiles from an example run consisting of 500 trials of 60-year-long simulations.



forecast skills, respectively (Fig. 3d), again averaging across smolt recruitment models.

The 90th percentile of harvest response to diminishing forecast skill (Fig. 4) was similar to mean harvest response. Under the A13a and A13b strategies, the 90th percentile experienced a ~7% and ~12% reduction for Fair and Poor forecast skills, respectively. For the 50 000 spawner goal, the

90th percentile harvest was reduced by about 10% at the Poor forecast skill. With a 200 000 spawner target, the reductions were about 12%, 23%, and 43%, at the Good, Fair, and Poor forecast skills, respectively.

Changes in the 10th percentile of harvest were largely undetectable under the A13a and A13b strategies (Fig. 5). On the other hand, diminishing forecast skill had a dramatic effect under CE50; decreases in the 10th percentile ranged from 5%–20% for Good forecast skill to 30%–90% for Poor forecast skill, depending on the smolt recruitment model. Under the CE200 strategy, the 10th percentile of harvest was zero, so the relative change in harvest was undefined.

The effect of diminishing forecast skill on the conservation metric (frequency of falling below the critical spawner density threshold) varied only slightly by subaggregate under the A13 strategies. Under the constant escapement strategies, the North–Central subaggregate showed generally the most sensitivity to forecast skill, so we focus our analyses on that subaggregate.

There was no detectable effect of forecast skill on the frequency of the North–Central subaggregate falling below the critical spawner density threshold under the A13a strategy, though under strategy A13b there was a detectable but very minor (1%–2%) increase in that frequency at the lowest forecast skill (Fig. 6b). The greatest effect of forecast skill was seen under the CE50 strategy, where the absolute changes in frequency were +2%, +6%, and +11% for Good, Fair, and Poor forecast skill, respectively (Fig. 6c). At 200 000 target spawners, only the simulations with the Ricker smolt recruitment model showed any substantial increase in frequency of critical spawner abundance with diminishing skill (Fig. 6d).

The overall trends in sensitivity to forecast skill discussed above were shared by the two smolt recruitment models. However, the magnitude in sensitivity was highly variable among the two models in some cases, in particular under the constant escapement strategies for both critical spawner abundance and the 10th percentile of harvest. In these cases, the Ricker model typically showed the most sensitivity to forecast error. This behavior is a product of the overcompensation in the Ricker function. Smolt production will be low at both low and high spawner abundances, increasing the frequency of low adult recruitment with respect to the Beverton–Holt model. The higher sensitivity of the Ricker model to forecast error occurs because the error will result in overharvest at low adult abundances and underharvest at very high abundances, both of which lead to lower smolt recruitment compared with an error-free forecast.

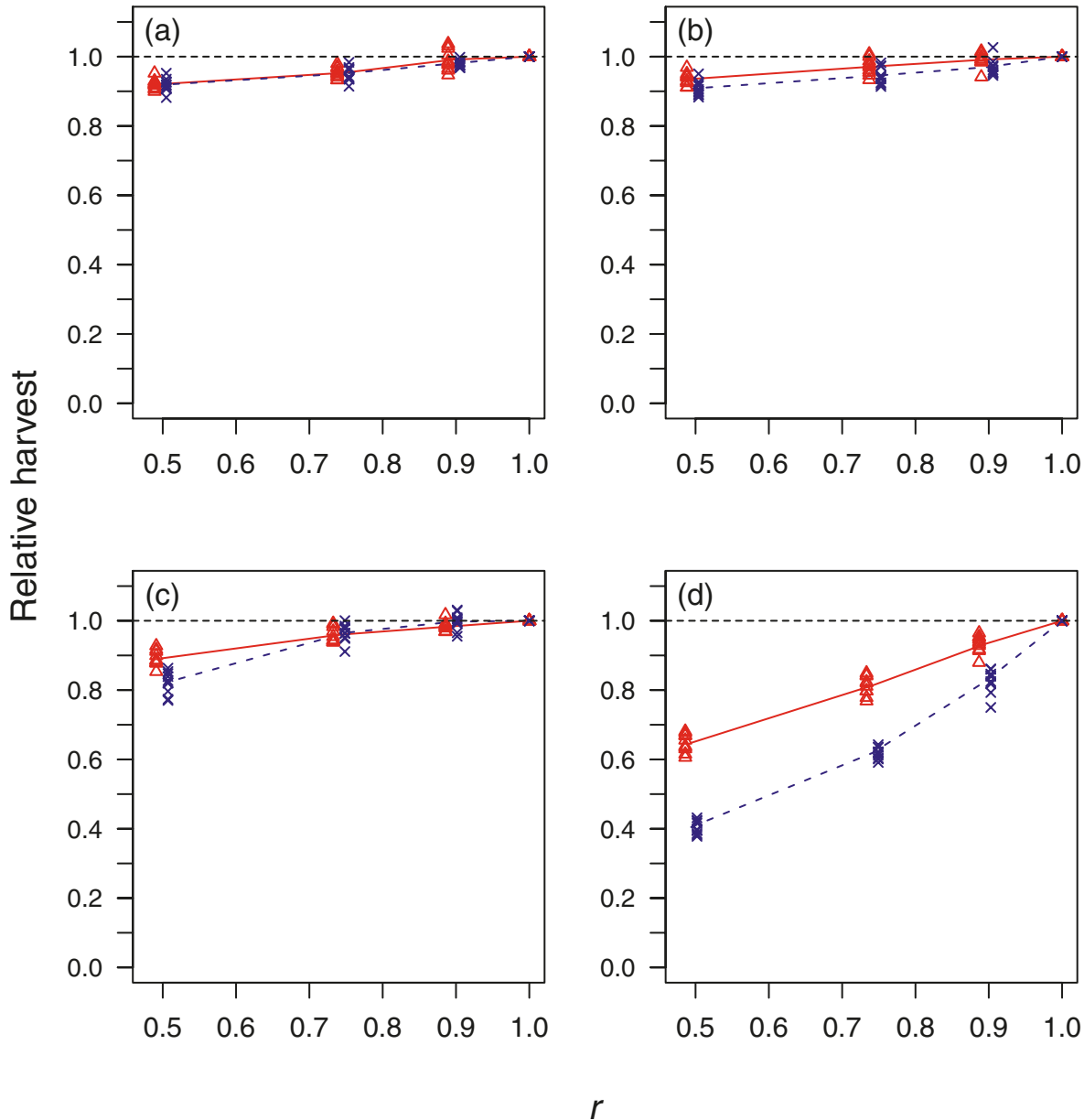
## Discussion

The most striking result of this study is the lack of sensitivity of the A13 management strategy performance to marine survival forecast error. An examination of the A13a decision matrix helps explain why this is so. We consider first the annual harvest, followed by the frequency of falling below the critical spawner density threshold.

Mean annual harvest will be highly influenced by the years with high adult recruitment because of the skewed abundance distribution and the progressive harvest rates in the decision matrix. High adult recruitment is more likely to occur when the parent spawner status is “High” and the marine survival



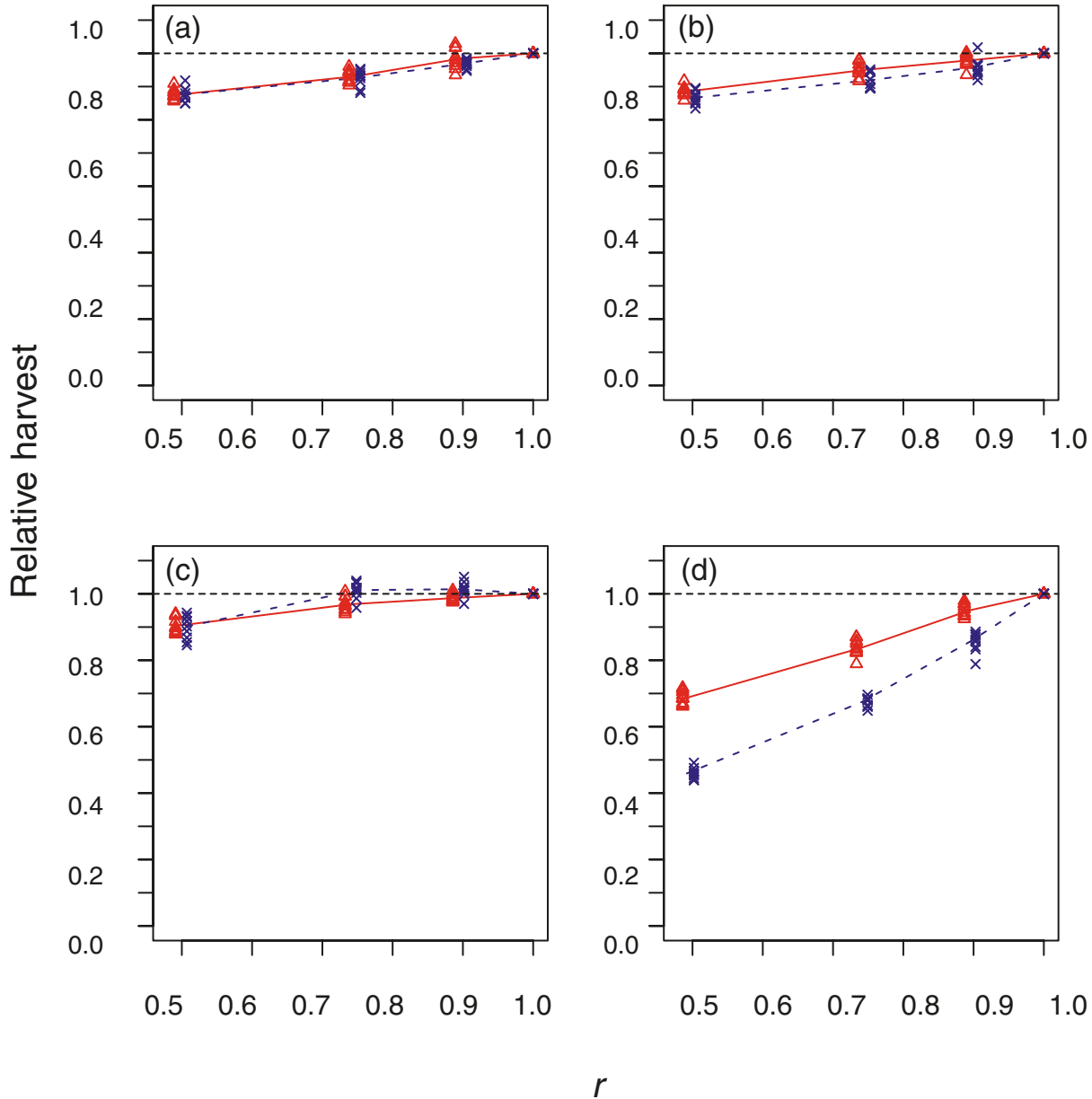
**Fig. 3.** Mean annual harvest under the (a) A13a, (b) A13b, (c) CE50, and (d) CE200 management strategies for various levels of forecast skill ( $r$ ) using the Beverton–Holt model (solid line and open triangles) and Ricker model (dashed line and letter “x”). Values of the mean are relative to the mean for a Perfect forecast ( $r = 1$ ). Forecasts were either of log-transformed marine survival rate (A13a and A13b) or log-transformed adult recruitment (CE50 and CE200). Forecast skill is given as the mean Pearson’s correlation coefficient between actual and forecasted values. Symbols represent the results from 10 different parameter sets for each spawner–smolt model. Symbols from each model are offset slightly along the horizontal axis so they are distinguishable. Lines give the mean result from the 10 parameter sets. For each parameter set, 500 trials of 60-year runs were performed.



rate is also “High”. (We say “more likely” because low survival from egg to smolt to adult can still cause low adult recruitment even when both parent spawner abundance and marine survival rate are high.) When the actual parent spawner status and marine survival rate place us in the upper right cell of the A13a decision matrix, imperfect forecasts can only move us leftward in the matrix (if they move us at all), which is towards smaller harvest rates. This, of course, results in lower harvest. The greatest departure from the intended result would occur when the current system state implied a 45% harvest rate, but we applied an 8% harvest rate.

However, such a scenario is very rare. As an example, we ran a 30 000-year simulation with the A13a strategy and Beverton–Holt model imposed and the forecast skill as Poor. The joint frequency of “High” parent spawner status and “High” marine survival rate was 6.7%. For these years, the harvest rate should have always been 45%. However, forecast error meant the chosen harvest rate could potentially have been 8%, 15%, 30%, or 45%. In fact, for this example, when the population state was “High” parent spawner status and “High” marine survival, the conditional frequency distribution of applied harvest rates was 0%, 7%, 45%, and 48% for

**Fig. 4.** 90th percentile of annual harvest under the (a) A13a, (b) A13b, (c) CE50, and (d) CE200 management strategies for various levels of forecast skill ( $r$ ) using the Beverton–Holt model (solid line and open triangles) and Ricker model (dashed line and letter “x”). Values of the 90th percentile are relative to the values under a Perfect forecast ( $r = 1$ ). Forecasts were either of log-transformed marine survival rate (A13a and A13b) or log-transformed adult recruitment (CE50 and CE200). Forecast skill is given as the mean Pearson’s correlation coefficient between actual and forecasted values. Symbols represent the results from 10 different parameter sets for each spawner–smolt model. Symbols from each model are offset slightly along the horizontal axis so they are distinguishable. Lines give the mean result from the 10 parameter sets. For each parameter set, 500 trials of 60-year runs were performed.

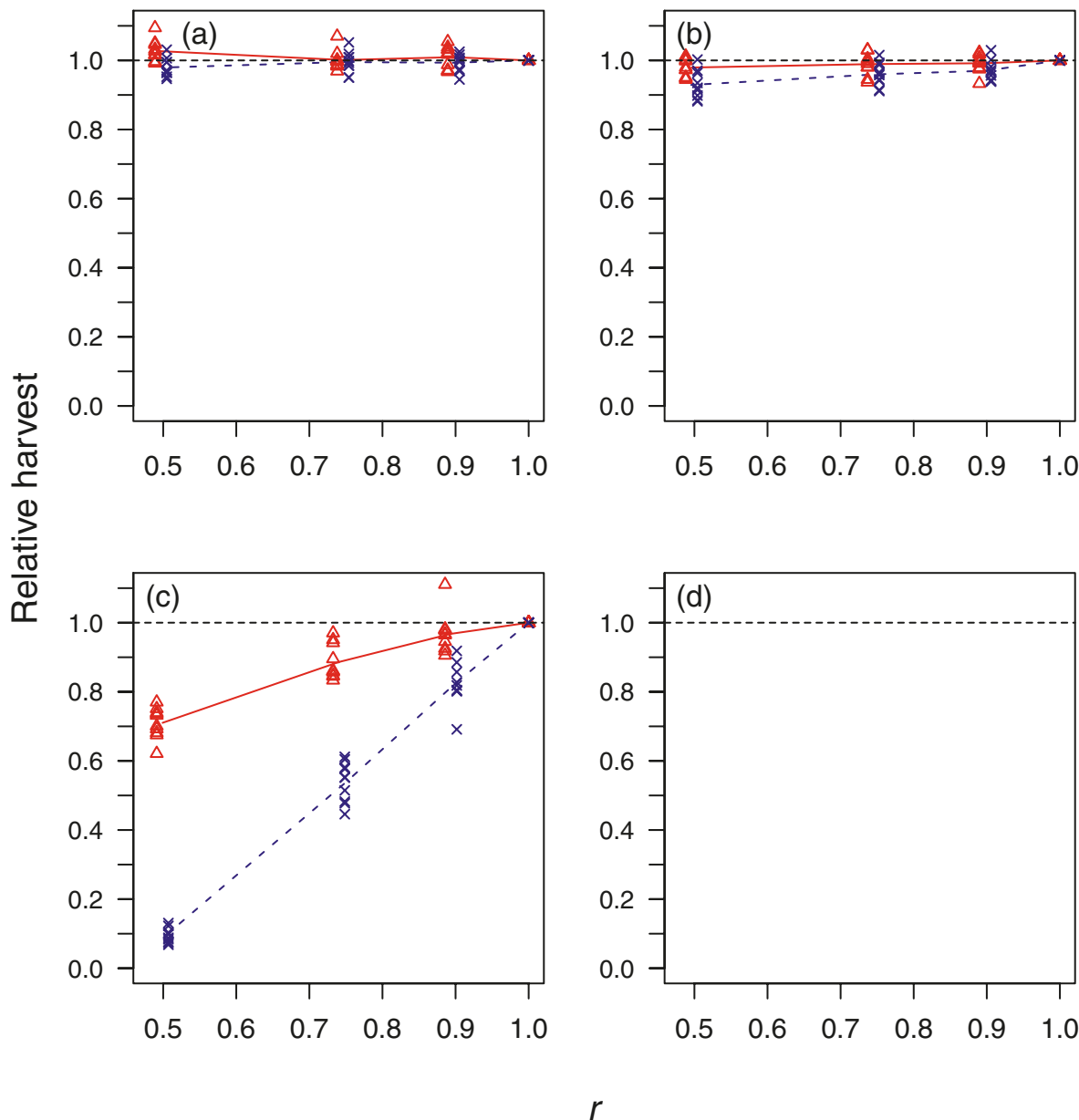


harvest rates of 8%, 15%, 30%, and 45%, respectively. Thus, in no case was the harvest rate severely under-applied (the 8% harvest rate), though in 45% of the years we applied a harvest rate of 30% instead of 45%. The end result was that harvest rates were on average only moderately under-applied when adult recruitment was high even when forecast skill was Poor.

The reason that the frequency of critical spawner abundance is relatively insensitive to forecast error under the A13 strategies is more easily understood. The condition that leads to critically low spawner densities is very low adult recruit-

ment, and very low adult recruitment is more likely to occur when the marine survival rate is “Extremely Low” and when parent spawners were few in number (in the “Very Low” or “Critical” categories). These conditions place us in the lower left portion of the decision matrix, so forecast error can only move us rightward along the marine survival axis, if anywhere. However, the harvest rate would remain unchanged if the parent spawner status were Critical (it remains at 8%) or only marginally if the parent spawner status were Very Low (the harvest rate increases from 8% to 11%). In summary, no matter how large our marine survival forecast error is, our

**Fig. 5.** 10th percentile of annual harvest under the (a) A13a, (b) A13b, (c) CE50, and (d) CE200 management strategies for various levels of forecast skill ( $r$ ) using the Beverton–Holt model (solid line and open triangles) and Ricker model (dashed line and letter “x”). Values of the 10th percentile are relative to the values under a Perfect forecast ( $r = 1$ ). Forecasts were either of log-transformed marine survival rate (A13a and A13b) or log-transformed adult recruitment (CE50 and CE200). Forecast skill is given as the mean Pearson’s correlation coefficient between actual and forecasted values. Symbols represent the results from 10 different parameter sets for each spawner–smolt model. Symbols from each model are offset slightly along the horizontal axis so they are distinguishable. Lines give the mean result from the 10 parameter sets. For each parameter set, 500 trials of 60-year runs were performed. Symbols are absent from panel (d) because the 10th percentile harvest with Perfect forecast skill was zero; thus, the relative harvest is undefined.



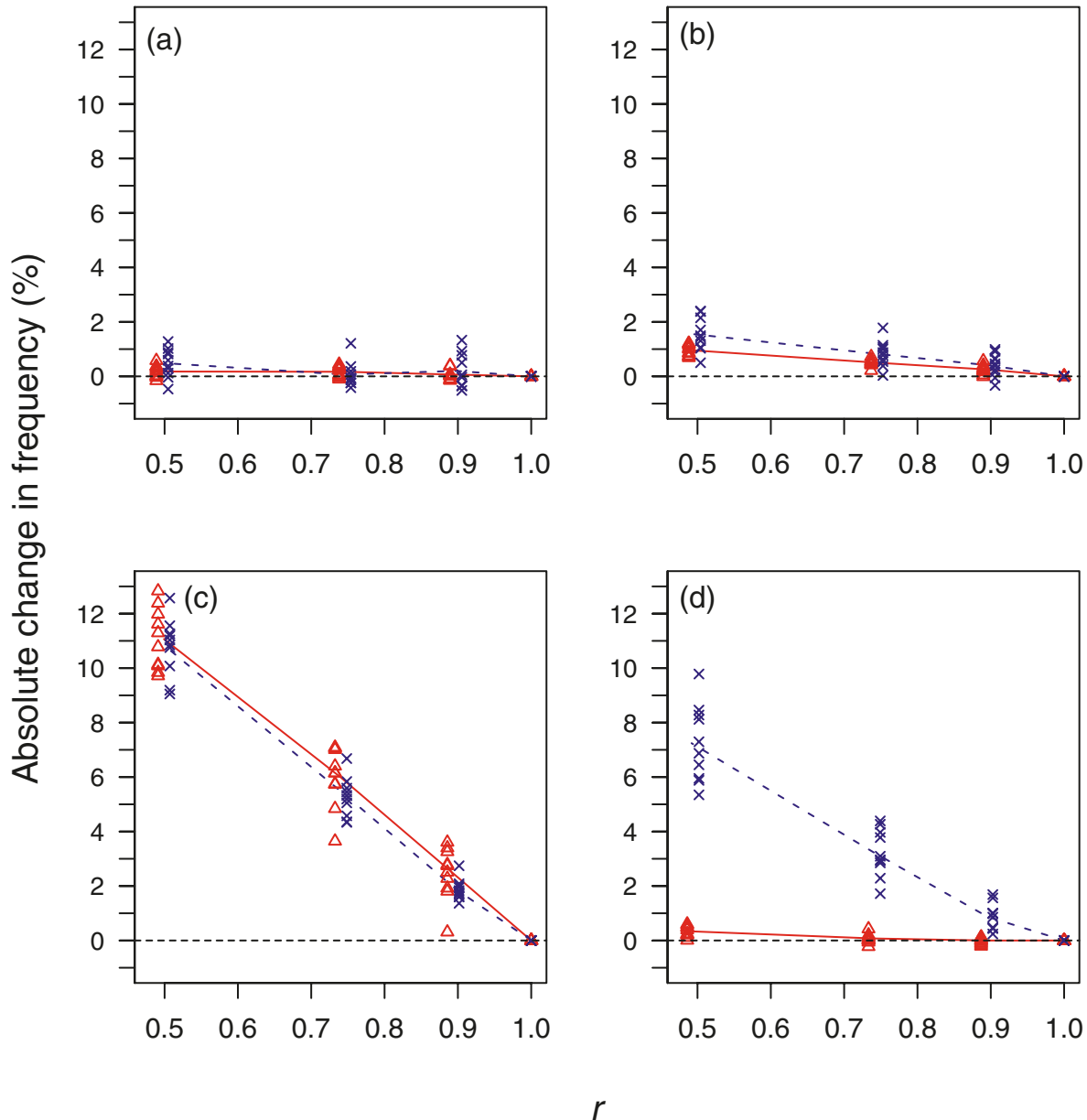
prescribed harvest rates will always be low when parent spawner status is Very Low or Critical. Only when the parent spawner densities are high across all subaggregates, freshwater mortality is great, marine survival is low, and we mistakenly assume marine survival to be high, do we risk allowing too high of a harvest impact rate.

Under the A13 strategies, only about a 5% increase in long-term harvest would be gained from a substantial improvement in forecast skill (i.e., from our Poor to Good classification). The absolute reduction in frequency of falling

below critical spawner densities would be less than 1% by equally improving the forecast skill. Research towards improving forecast skill could be justified on economic grounds if the cost of the research were less than the financial benefit from the 5% harvest increase.

However, there is another issue to consider, and that is the probability of observing the benefit of the improved forecast skill during the lifetime of an imposed management strategy. We have chosen a 60-year time frame for implementation of a management strategy under a given forecast skill, which is

**Fig. 6.** Frequency of North–Central subaggregate spawner abundances falling below critical seeding targets under the (a) A13a, (b) A13b, (c) CE50, and (d) CE200 management strategies for various levels of forecast skill ( $r$ ) using the Beverton–Holt model (solid line and open triangles) and Ricker model (dashed line and letter “x”). Frequencies are given as the difference in frequency from that of a Perfect forecast ( $r = 1$ ). Forecasts were either of log-transformed marine survival rate (A13a and A13b) or log-transformed adult recruitment (CE50 and CE200). Forecast skill is given as the mean Pearson’s correlation coefficient between actual and forecasted values. Symbols represent the results from 10 different parameter sets for each spawner–smolt model. Symbols from each model are offset slightly along the horizontal axis so they are distinguishable. Lines give the mean result from the 10 parameter sets. For each parameter set, 500 trials of 60-year runs were performed.

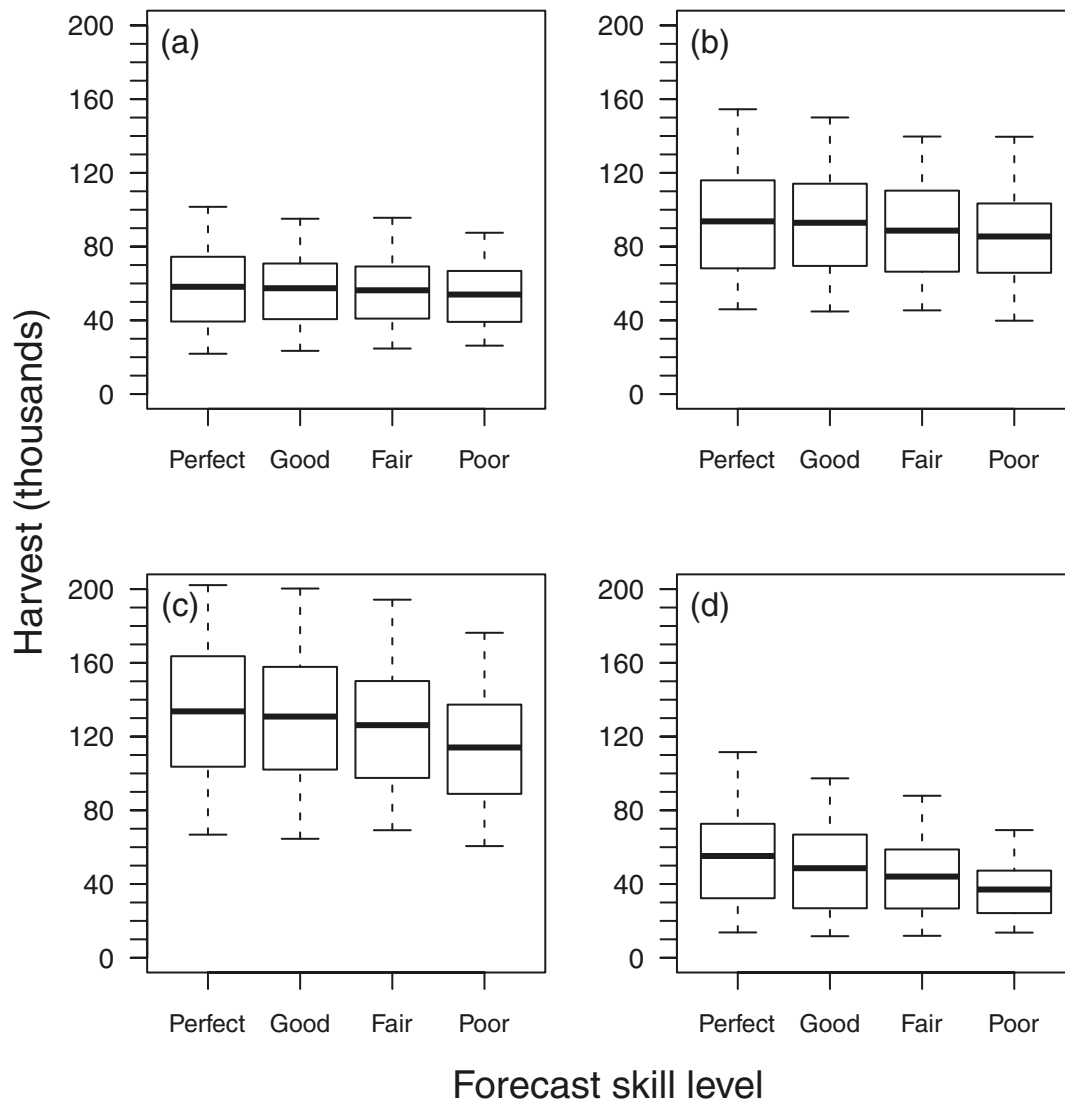


an optimistically long time to expect a management strategy to be enforced without alteration. If we look at not only the mean of each performance metric taken over 500 trials of 60-year runs, but also the variability among the trials, we see large variability in the performance metrics, which will make attempts to verify the positive effects of forecast improvement more difficult (Figs. 7 and 8). For harvest, it is evident qualitatively that where the objective is a constant spawner escapement, we are more likely to see a response from an improvement in forecast skill (assuming we had the luxury

of 120 years to perform the experiment). The quantitative probability of observing **any** increase in mean annual harvest following a substantial improvement in forecast skill (e.g., from Poor to Good) is still only about 60%. In contrast, under the A13 strategies, the odds of seeing positive results from our efforts are never much better than 50/50. The probabilities of observing an increase in mean annual harvest following an improvement in forecast skill for all the management strategies is given (Table 7).

Similar to the case of harvest, we are unlikely to observe a

**Fig. 7.** Mean of annual harvest over a 60-year period under the A13a, A13b, CE50, and CE200 management strategies for various forecast skills. Forecasts were either of log-transformed marine survival rate (A13a and A13b) or log-transformed adult recruitment (CE50 and CE200). Forecast skill, given here as the mean correlation coefficient between actual and forecasted values, was 1, 0.9, 0.75, and 0.5 for Perfect, Good, Fair, and Poor skill levels, respectively. Bar-and-whisker plots give the mean and 5th, 25th, 75th, and 95th percentiles of mean annual harvest from 500 trials. Smolt production was simulated with the stochastic Beverton–Holt model.



**Table 7.** Probability (%) of observing an increase in mean annual harvest following improvement in forecast skill under various management strategies.

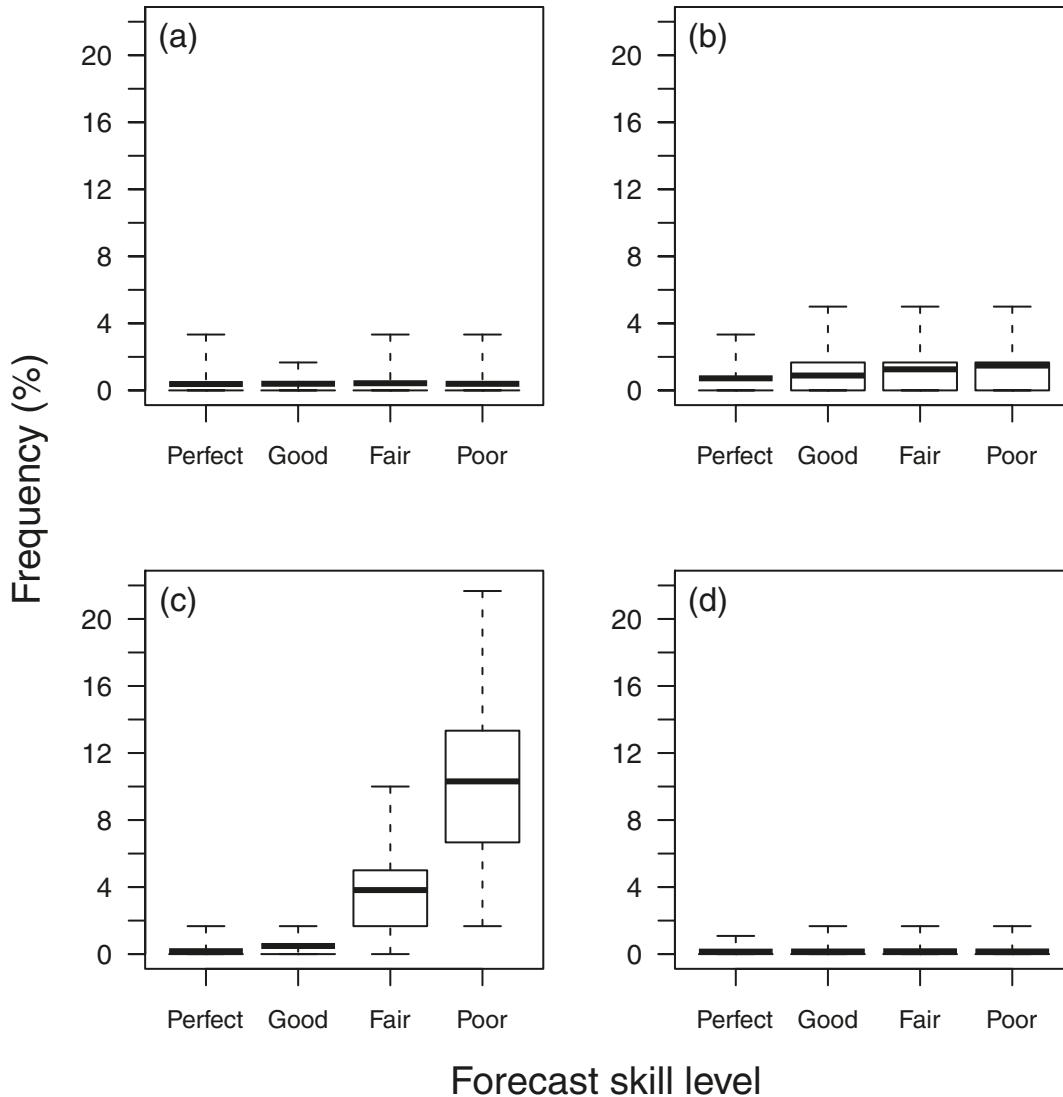
Management strategy	Improvement in forecast skill					
	Poor→Fair	Poor→Good	Poor→Perfect	Fair→Good	Fair→Perfect	Good→Perfect
A13a	52	53	55	51	52	51
A13b	53	56	56	53	53	≤50
CE50	60	60	65	52	56	51
CE200	59	61	67	53	59	55

**Note:** Probabilities are based on 60 years of observation each with the old and new forecast skill. Smolt recruitment was simulated with the Beverton–Holt model.

decrease in the frequency of falling below critical spawner densities following a substantial improvement in forecast skill when using the A13 strategies (Fig. 8; Table 8). This is because forecast skill had so little effect on this conservation metric under either A13 strategy. This is not the situation for

the constant escapement strategy with a low escapement target, however. For example, if we improve the forecast skill from Poor to Good, we have a 98% probability of seeing a positive response when the target is 50 000 spawners. In contrast, when the escapement target is large (200 000 spawners),

**Fig. 8.** Frequency of North–Central subaggregate spawner abundance falling below critical seeding targets over a 60-year period under the A13a, A13b, CE50, and CE200 management strategies for various forecast skills. Forecasts were either of log-transformed marine survival rate (A13a and A13b) or log-transformed adult recruitment (CE50 and CE200). Forecast skill, given here as the mean correlation coefficient between actual and forecasted values, was 1, 0.9, 0.75, and 0.5 for Perfect, Good, Fair, and Poor skill levels, respectively. Bar-and-whisker plots give the mean and 5th, 25th, 75th, and 95th percentiles of mean annual harvest from 500 trials. Smolt production was simulated with the stochastic Beverton–Holt model.



**Table 8.** Probability (%) of observing a decrease in mean frequency of falling below critical spawner density threshold following an improvement in forecast skill under various management strategies.

Management strategy	Improvement in forecast skill					
	Poor→Fair	Poor→Good	Poor→Perfect	Fair→Good	Fair→Perfect	Good→Perfect
A13a	≤50	50	51	50	51	51
A13b	53	61	64	57	60	53
CE50	83	98	98	87	91	56
CE200	51	50	52	≤50	50	51

**Note:** Probabilities are based on 60 years of observation each with the old and new forecast skill. Smolt recruitment was simulated with the Beverton–Holt model.

there is miniscule chance of observing any positive response to a change in forecast skill

Though insensitivity to forecast error was not an explicit design criterion when the A13 strategy was devised, we have

demonstrated that the particular choice of harvest rates within the decision matrix makes it very forgiving to poor forecast skill. Others have also found mean harvest or economic return to be largely insensitive to forecast skill for different

types of salmon management strategies (Costello et al. 1998; Kaje and Huppert 2007). While it may be tempting to say that such insensitivity is the result of conservative management strategies (such as the A13 cases where the aim was to rebuild a stock to head off a pending Endangered Species Act listing), not all these strategies were as heavily driven by conservation objectives. Costello et al. (1998), in fact, optimized management to maximize the net value of the Pacific Northwest salmon fishery, whereas Kaje and Huppert (2007) aimed at meeting wild coho spawner escapement goals that maximized smolt production while meeting tribal treaty obligations.

Escapement goal management proved to be much more sensitive to forecast error than the A13 strategy. In addition, consequences of escapement goal management depended on the relationship between the goal and the productivity, given as typical adult recruitment, of the population. With a low goal (CE50), mean annual harvest was little affected by forecast quality, while critical seeding targets were often not achieved in the poor forecast simulations. By contrast, with a high goal (CE200), harvest was reduced with poor forecasts, while the probability of achieving critical seeding levels depended, in our modeling, on assumptions about the smolt recruitment relationship (Ricker or Beverton–Holt).

Although it was not the main focus of our analysis, we show escapement goal management to be sensitive not only to forecast error, but also to the relationship between the goal and the productivity of the stock and to the stock's population dynamics. By contrast, the exploitation rate strategy in A13 was more robust to imperfect knowledge. Exploitation rate harvest, in general, tends to be implemented through controls on fishing effort rather than harvest quotas. Effort management tends to be self-correcting; catch rates vary with stock abundance, reducing the likelihood of overharvest if the forecast is too high and allowing the harvest of more fish than expected if the forecast is low.

Results such as these highlight that care should be taken when generalizing results from particular case studies. They also demonstrate the utility of the MSE approach, which is perfectly suited to exploring under which types of strategies forecast error plays a major role on performance. Preferably, management strategy evaluations would consider a suite of factors affecting strategy performance (e.g., Dichmont et al. 2006) to determine which factors were most important and most subject to improvement. In the end, when allocating scarce resources for management, it may be more productive to focus on areas other than forecasting, such as monitoring (Walters and Collie 1988) or implementing in-season flexibility in harvest (Walters 1989).

With increasing pressures on Pacific salmon habitats (Bottom et al. 2009), harvest management will increasingly need to balance harvest opportunities with conservation risks. Management strategy evaluation is a powerful modeling tool for identifying management strategies that balance harvest and conservation and are robust to environmental variation, incomplete knowledge of population dynamics, and forecast uncertainty.

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## Appendix A. Smolt abundance time series reconstruction

We reconstructed smolt abundance time series from



(i) OCN adult recruitment estimates and (ii) estimates of OCN marine survival reconstructed from estimates of OPIH marine survival. The time series of OPIH marine survival was calculated as total number of adult hatchery coho salmon (catch plus escapement) divided by the number of hatchery smolts released (Pacific Fishery Management Council 2003, 2010).

To derive an OCN marine survival time series from the OPIH marine survival time series, we first compared estimates of OPIH marine survival with estimates of wild marine survival for a small number of Oregon coast watersheds where smolts have been surveyed during recent years. The wild marine survival estimates were calculated from Oregon Department of Fish and Wildlife surveys of coho smolts and female and male spawners at up to seven life cycle monitoring (LCM) sites (Suring et al. 2009). The data from the LCM sites were used to construct a time series of wild marine survival from 1998 to 2009. Fishery exploitation rates were assumed to be equivalent across LCM sites when estimating adult recruits from spawner counts.

A linear regression of LCM marine survival ( $S_{LCM}$ ) against OPIH marine survival ( $S_{OPIH}$ ) for the overlapping years ( $n = 12$ ) gave an  $R^2$  of 0.62. Because the intercept was not significantly different from 0 ( $p$  value = 0.737), we regressed  $S_{LCM}$  against  $S_{OPIH}$  with the intercept fixed at 0 for overlapping years to obtain a ratio  $S_{LCM}/S_{OPIH} = 2.41$ . This ratio was multiplied against the entire  $S_{OPIH}$  time series to obtain a time series for OCN coho marine survival ( $S_{OCN}$ ) for the years 1970–2009.

OCN smolt numbers were calculated by dividing the total number of OCN adults by the derived OCN marine survival. This resulted in ratios of OCN smolts per parent spawner for the adult return years 1993–1996 that exceeded 140 smolts/spawner, ratios deemed to be unrealistically high as also noted by Lawson et al. (2004). Furthermore, mean smolt numbers were calculated to be 2.63 times higher during adult return years 1993–1996 than during all other years on average. The years 1993–1996 were also those years when OPIH marine survival rates were the lowest on record. We corrected for what we believed to be unreasonable smolt abun-

dances by dividing the smolt numbers in 1993–1996 by 2.63 and then back-calculated marine survival for those years to arrive at final derived time series of OCN marine survival. The final OCN marine survival estimates were used to generate a smolt abundance time series for each of the subaggregate populations by dividing subaggregate adult abundances by  $S_{OCN}$ ; thus, we assumed uniform marine survival for all OCN coho subaggregates.

Although the above adjustment was ad hoc, our analysis does not require the precise smolt production in any given year; rather, these derived estimates are only used to generate a time series from which to estimate model parameters for subsequent use in Monte Carlo simulations. In essence, we only need parameters that result in simulated populations that reasonably approximate the dynamics of real populations.

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