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[Article]

Retrospective Evaluation of Preseason Forecasting Models for Pink Salmon

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Abstract.—Models for making preseason forecasts of adult abundance are an important component of the management of many stocks of Pacific salmon *Oncorhynchus* spp. Reliable forecasts could increase both the profits from fisheries and the probability of achieving conservation and other management targets. However, the predictive performance of salmon forecasting models is generally poor, in part because of the high variability in salmon survival rates. To improve the accuracy of forecasts, we retrospectively evaluated the performance of eight preseason forecasting models for 43 stocks of pink salmon *O. gorbuscha* over a total of 783 stock-years. The results indicate that no single forecasting model was consistently the most accurate. Nevertheless, across the 43 stocks we found that two naïve time series models (i.e., those without explicitly modeled mechanisms) most frequently performed best based on mean raw error, mean absolute error, mean percent error, and root mean square error for forecasts of total adult recruits. In many cases, though, the best-performing model depended on the stock and performance measure used for ranking. In 21% of the stocks, a new multistock, mixed-effects stock–recruitment model that included early-summer sea surface temperature as an independent variable along with spawner abundance demonstrated the best performance based on root mean square error. The best-performing model for each pink salmon stock explained on average only 20% of the observed variation in recruitment. Owing to the uncertainty in forecasts, a strong precautionary approach should be taken to achieve conservation and management targets for pink salmon on the West Coast of North America.

Preseason forecasts are an important component of harvesting and management systems for many stocks of Pacific salmon *Oncorhynchus* spp. Forecasts are used by management agencies to help decide on the fishing restrictions that will be necessary to achieve spawning escapement goals, especially early in the season before other information on abundance becomes available. In some cases, forecasts are also used by the fishing industry to regionally allocate harvesting and processing equipment and personnel. Unfortunately, because interannual variation in survival and recruitment rates can be large (Peterman 1987; Adkison et al. 1996), the predictive performance of salmon forecasting models is generally poor (Adkison and Peterman 2000), especially for pink salmon *O. gorbuscha* (Adkison 2002). This lack of forecasting accuracy translates into economic losses for the fishing industry and errors in achieving escapement targets for management agencies (Eggers 1993). Years in which the forecasted recruitment of adult salmon is overestimated generally produce fewer spawners than desired. The early-season fishing plan in such years tends to be aggressive, and by the time in-season estimates indicate fewer recruits than expected it is too late to reduce harvest rates enough to achieve the target abundance of spawners. The converse tends to occur when recruitment is underestimated (Bocking and Peterman 1988). Besides reducing spawner abundance, persistent overfishing early in the season can also erode the genetic diversity associated with run timing (e.g., Allendorf et al. 1987).

Models of varying complexity and sophistication have been proposed and used for preseason forecasting of salmon returns on the West Coast of North America. These models range from simple moving-average time series models (Wood et

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al. 1997) to complex stock–recruitment models that incorporate environmental variables (Adkison 2002) or models based on neural networks (Zhou 2003). In some cases, forecasts are based in part on fry or smolt abundance. These models have had varying success. Performance is generally poor, especially when more recent data are used or when data on stocks other than those originally used to derive a model are later applied to judge its performance (Myers 1998).

To compare all forecasting models on an equal basis and to broadly evaluate their performance across many stocks, we conducted a retrospective analysis of eight models across 43 pink salmon stocks in the northeastern Pacific over 783 stock-years. Retrospective analysis, a form of cross validation, is a rigorous method for evaluating the performance of forecasting models (Shao 1993). It entails using only the data that would have been available up to a given year to fit a model and make forecasts, which are then compared with the subsequent observations. The process is repeated iteratively, adding data for one more year at each step to measure how well a forecasting model would have performed for each year if it had been used historically. Various measures then summarize the performance of each model across years.

For retrospective evaluation, we selected from the numerous classes of models that have been used to forecast Pacific salmon returns. Two were simple time series models that did not explicitly incorporate biological or environmental data, and the others were more complex. As an example of the latter, we evaluated the forecasting performance of a multistock, mixed-effects Ricker stock–recruitment model that incorporated summer sea surface temperature (SST), capitalizing on the recent work of Mueter et al. (2002a). We also evaluated the single-stock Ricker stock–recruitment model, along with versions of the Ricker model that incorporated SST as an environmental variable and that incorporated autocorrelation in model residuals. In addition, we considered the Ricker model cast in the context of a Kalman filter to allow the Ricker *a* parameter to vary over time, a method that has shown promise in tracking changes in salmon productivity (Peterman et al. 2000, 2003). Averaging the forecasts of two or more individual models has also been used to generate preseason forecasts of salmon abundance (Fried and Yuen 1987) or harvests (Adkison 2002). Therefore, we also examined a forecast-averaging model. Finally, we ranked the models using several commonly used performance measures that quantify central tendency and the variability in the distribution of forecasting errors. The best model was defined as the one with the smallest forecasting errors according to each performance measure.

Methods

Data.—We compiled data on spawner abundance (*S*) and recruits (*R*) for 43 pink salmon stocks in the northeastern Pacific that were distributed from Northwest Alaska to Northwest Washington, including British Columbia (Table 1). The data on spawner abundance included both males and females. Recruits included both the catch and spawning escapement of both sexes. The time series for spawner abundance and recruits ranged from 17 to 47 years in duration, with an average of 29 years. Further details on the sources of data and their compilation can be found in Pyper et al. (2001).

With pink salmon stocks it is common to see a large difference in abundance between even- and odd-year returns within a given river system. To determine whether to pool even- and odd-year data, we conducted a stock–recruitment analysis to test whether this pattern was attributable mainly to differences in productivity (recruits/spawner) or to differences in the abundance of spawners. Ten stocks contained only even-year or only odd-year data, so comparing the productivities between cycle lines was not possible in those cases. Among the remaining 33 stocks, 25 (76%) showed no significant differences in productivity between the even- and odd-year cycle lines, but spawner abundances were different. We therefore concluded that the differences in productivity between the even- and odd-year lines were negligible for the majority of stocks and subsequently combined data from both lines in our stock–recruitment analyses. As shown in Results, we also pooled the even- and odd-year data for areas in which both cycle lines were present because we found that when we estimated separate productivities for each cycle line, forecasting ability was much poorer, possibly due to the imprecision in productivity estimates caused by smaller sample sizes.

Summer SST has been identified as an environmental variable that helps to explain the variation in survival rates of Pacific salmon (Mueter et al. 2002b). Summer SST data were compiled from the Comprehensive Ocean–Atmosphere Data Set (http://www.cdc.noaa.gov/coads/) and summarized using the methods outlined in Mueter et al. (2002a). The data used in our forecasting models represent the SST anomalies from long-term

TABLE 1.—Summary of data sets for 43 wild pink salmon stocks used in this analysis of forecasting models. N is the number of complete brood years available. Table is adapted from Pyper et al. (2001).

Region	Stock number	Stock or district	Brood years	N	Source[a]
Washington	1	Nooksack[b]	1959–1995	19	1
	2	Skagit[b]	1959–1995	19	1
	3	Stillaguamish[b]	1959–1995	19	1
	4	Snohomish[b]	1959–1995	19	1
	5	Puyallup River[b]	1959–1995	19	1
	6	Hood Canal[bc]	1959–1995	19	1
	7	Dungeness[b]	1959–1995	19	1
Fraser River	8	Total[b]	1957–1995	20	2, 3
Mainland British Columbia	9	Statistical Areas 12, 13, 15, 16[d]	1954–1994	21	4, 5
Central British Columbia	10	Statistical Area 10	1950–1995	46	6, 7
	11	Statistical Area 9	1950–1996	47	6, 7
	12	Statistical Area 8	1950–1996	47	6, 7
Northern British Columbia	13	Statistical Area 6	1950–1995	46	6, 7
	14	Statistical Area 2E	1950–1995	46	6, 7
Southeast Alaska	15	Southern (Districts 101–108)	1960–1996	37	8
	16	Northern Inside (Districts 109–112, 114, 115)	1960–1996	37	8
	17	Northern Outside (District 113)	1960–1996	37	8
Yakutat	18	Situk River	1962–1990	25	8, 9
	19	Humpy Creek	1962–1992	22	8, 9
Prince William Sound	20	Eastern District	1967–1996	30	10
	21	Montague District	1971–1996	26	10
	22	Southeastern District	1967–1996	30	10
Lower Cook Inlet	23	Southern District[e]	1960–1996	37	11
	24	Outer District[f]	1960–1996	37	11
	25	Kamishak District[g]	1960–1996	34	11
Kodiak Island	26	Afognak District	1980–1996	17	12
	27	Westside District	1980–1996	17	12
	28	Alitak District	1980–1996	17	12
	29	Eastside-Northend District	1980–1996	17	12
	30	Mainland District	1980–1996	17	12
Chignik	31	Chignik Bay District	1962–1995	31	13, 14
	32	Central District	1962–1995	34	13, 14
	33	Eastern District	1962–1995	34	13, 14
	34	Western District	1962–1995	34	13, 14
	35	Perryville District	1962–1995	34	13, 14
Alaska Peninsula	36	Northwestern District	1962–1996	35	13, 15
	37	Southeast and South-central districts	1962–1996	35	13, 16
	38	Southwest and Unimak districts	1962–1996	35	13, 16
Bristol Bay	39	Nushagak District[h]	1960–1996	17	17
Norton Sound	40	Nome	1978–1995	17	18, 19
	41	Golovin	1968–1995	18	18, 19
	42	Moses Point and Norton Bay	1963–1994	24	18, 19
	43	Unakleet	1962–1995	23	18, 19

[a] 1. Jeff Haymes, Washington Department of Fish and Wildlife, Olympia; 2. Al Cass, Canadian Department of Fisheries and Oceans (DFO). Nanaimo, British Columbia (B.C.); 3. Jim Woodey, Pacific Salmon Commission, Vancouver, B.C.; 4. Clyde Murray, DFO, Nanaimo, B.C.; 5. Lia Bjesterveld, DFO, Vancouver, B.C.; 6. Dennis Rutherford, DFO, Nanaimo, B.C.; 7. Wood et al. (1999); 8. Tim Zadina, Alaska Department of Fish and Game (ADFG), Ketchikan; 9. Clark (1995); 10. Mark Willette, ADFG, Cordova; 11. Ted Otis, ADFG, Homer; 12. Kevin Brennan, ADFG, Kodiak; 13. Denby Lloyd, ADFG, Kodiak; 14. Owen and Sarafin (1999); 15. Murphy et al. (1999); 16. Campbell et al. (1999); 17. Michael Link, ADFG, Anchorage; 18. Betsy Brennan, ADFG, Anchorage; 19. Brennan et al. (1998). Except where a formal citation is given, all sources are personal communications.

[b] Data were only available for odd years (e.g., brood years 1959, 1961, . . ., 1995) because few if any pink salmon spawn in even years.

[c] Sum of Dosewallips, Duckabush, and Hamma Hamma data sets.

[d] Only even-year data were used because catches in most odd years were confounded by the catch of Fraser River pink salmon.

[e] Sum of Humpy Creek, Port Graham, and Seldovia Bay data sets.

[f] Sum of Port Chatham, Port Dick, Rocky River, and Windy Creek data sets.

[g] Sum of Brown's Peak Creek, Bruin River, and Sunday Creek data sets.

[h] Data were only available for even years because few if any pink salmon spawn in odd years.

means (in °C) at each location corresponding to the coastal areas occupied by the pink salmon stocks during their early ocean residence (April–July for stocks in Washington, British Columbia, and Southeast Alaska, May–August for most Alaska stocks, and June–September for stocks in Western Alaska; further details are available in Mueter et al. 2002a).

Models.—First, we used two naïve time series models to forecast recruits. These models did not explicitly include biological (spawner) or environmental variables as independent variables and did not require parameter estimation. They merely summarized recent information on adult recruits (returns) for pink salmon, which mature and return to freshwater slightly less than 2 years after being spawned. The first model [R(yr-2)] is

$$R_{\mathrm{yr}} = R_{\mathrm{yr}-2} + \varepsilon_{\mathrm{yr}}, \tag{1}$$

where R_{yr} is the forecasted returns for year yr, $R_{\mathrm{yr}-2}$ is the returns during year yr−2 (due to the 2-year life span of pink salmon), and $\varepsilon_{\mathrm{yr}}$ is the residual error, with $\varepsilon_{\mathrm{yr}} \sim N(0, \sigma^2)$. The second (2-year average) naïve model is

$$R_{\mathrm{yr}} = \frac{R_{\mathrm{yr}-2} + R_{\mathrm{yr}-4}}{2} + \varepsilon_{\mathrm{yr}}, \tag{2}$$

where R_{yr} is the forecasted return in year yr, $R_{\mathrm{yr}-2}$ and $R_{\mathrm{yr}-4}$ are the returns in years yr−2 and yr−4, and $\varepsilon_{\mathrm{yr}}$ is the residual error, with $\varepsilon_{\mathrm{yr}} \sim N(0, \sigma^2)$. This model thus averages recruitment for the particular ''line'' of pink salmon that matures every other year. Because of the 2-year life span of pink salmon, both naïve models are capable of taking into account the potentially different abundance of even- and odd-year lines. For both of the naïve models, we found that the normality assumption for the errors held in the majority (64%) of the stocks according to Kolmogorov–Smirnov tests for normality.

Next, we used three versions of the linearized, single-stock Ricker stock–recruitment function to forecast recruits. The first, referred to here as simply the Ricker model, is

$$\log(R_t/S_t) = a - bS_t + \varepsilon_t, \tag{3}$$

where a and b are estimated parameters, S_t is the abundance of spawners in brood year t, R_t is the abundance of adult recruits resulting from that number of spawners, and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. The second Ricker model incorporates a first-order autoregressive process for the residuals in equation (3), taking the form

$$\varepsilon_t = \varphi\varepsilon_{t-1} + \nu_t, \tag{4}$$

where φ is the estimated autocorrelation coefficient and $\nu_t \sim N(0, \sigma_\nu^2)$. We refer to equations (3) and (4) as the Ricker AR(1) model; it reflects the autocorrelation in residuals found in some species and stocks of salmon. The third Ricker model adds an effect of SST to equation (3):

$$\log(R_t/S_t) = a - bS_t + \gamma X_{t+1} + \varepsilon_t, \tag{5}$$

where γ is the estimated effect of SST on $\log(R_t/S_t)$, X_{t+1} is the summer SST anomaly at the location nearest the ocean-entry point of the stock in year $t + 1$, when pink salmon fry from brood year t migrated to the ocean, and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. This model is referred to as the Ricker SST model. In effect, model (5) replaces the unspecified source of autocorrelation in residuals in model (4) with SST as an explanatory variable.

We also evaluated a hierarchical model, which simultaneously utilizes information from multiple stocks of salmon. Conceptually, hierarchical models differ from standard single-stock models in a simple way. Each of the first five forecasting models described above is applied to data one stock at a time, whereas a hierarchical model takes advantage of the observed similarity among nearby stocks (Peterman et al. 1998; Pyper et al. 2001, 2002) in their interannual variation in survival rates arising from sharing similar environments. The hierarchical model that we evaluated as a forecasting tool was a multistock, mixed-effects version of the Ricker model that included SST as defined above. Mueter et al. (2002a) found that this model was useful for describing variations in salmon productivity (log[R/S]); it is referred to as the mixed-effects (ME) model and takes the following form:

$$\log(R_{it}/S_{it}) = \alpha + a_i - b_i S_{it} + \gamma X_{i,t+1} + g_i X_{i,t+1} + \varepsilon_{it}, \tag{6}$$

where $\log(R_{it}/S_{it})$ is the productivity of stock i resulting from brood year t, is a fixed intercept describing the productivity common to all pink salmon stocks in a given area (northern-area stocks or southern-area stocks, using the same delineation as Mueter et al. 2002a), and a_i is a random, stock-specific deviation from α describing the productivity of stock i relative to α. Similarly, γ is the fixed effect of SST on $\log(R_{it}/S_{it})$ common to all stocks and g_i is the random, stock-specific deviation from γ. The random effects a_i and g_i were assumed to follow a joint normal distribution with means of zero, variances σ_a^2 and σ_g^2, and covariance

σ_{ag}. Errors were assumed to be first-order autocorrelated within stocks and were modeled as $\varepsilon_{it} = \varphi\varepsilon_{i,t-1} + \nu_t$, with $\nu_t \sim N(0, \sigma_\nu^2)$. We considered this type of multistock model because it results in smaller bias and greater precision in parameter estimates than a model that is fit to each stock's data separately (Su et al. 2004).

Another single-stock model examined here recognized that parameters are not necessarily constant over time. Extensive Monte Carlo simulations demonstrated that the Kalman filter–random walk model showed promise in identifying and adjusting for temporal changes in salmon productivity (Peterman et al. 2000). We therefore applied a Kalman filter estimation method to the Ricker stock–recruitment model for forecasting purposes, which allowed for temporal changes in productivity (i.e., the *a* parameter). The model had two components. The first was the observation equation

$$\log(R_t/S_t) = a_t - bS_t + \varepsilon_t, \tag{7}$$

which is similar to equation (3) except that the *a* parameter is subscripted by *t*. The second component is the system equation

$$a_t = a_{t-1} + \nu_t, \tag{8}$$

where a_t is modeled as a random walk process with $\nu_t \sim N(0, \sigma_\nu^2)$. This model is referred to as the Kalman filter–random walk model (KF; for the details of its estimation, see Peterman et al. 2000). Other methods of tracking changes in the Ricker *a* parameter (annually updating model 3 above and applying Walters' [1990] bias correction) proved less effective than the Kalman filter (Peterman et al. 2000) and were therefore not evaluated here.

To generate forecasts of adult recruits, $\hat{R}_t$, each of the models that estimated $\log(R_t/S_t)$ required back-transformation to estimate the forecasted mean number of recruits on an arithmetic scale. Accounting for the well-known bias associated with back-transforming lognormally distributed variables (Hayes et al. 1995), forecasts were generated using the equation

$$\hat{R}_t = \exp\left(\hat{y}_t + \frac{\sigma^2}{2}\right) \times S_t, \tag{9}$$

where $\hat{R}_t$ is the forecast of the mean number of recruits resulting from brood year *t*, $\hat{y}_t$ is the estimate of $\log(R_t/S_t)$, and σ^2 is the variance of the residuals. For the Ricker, Ricker SST, and KF models, σ_ε^2 was used in equation (9). For the Ricker AR(1) model, the residual variance after accounting for autocorrelation, σ_ν^2 (equation 4), was used in equation (9). For the ME model, we applied equation (9) by estimating the within-stock residual variance (i.e., σ_i^2, consistent with the notation of equation 6) rather than the overall residual variance after accounting for autocorrelation, σ_ν^2, which was estimated based on all stocks combined.

Preseason salmon forecasts have also been generated by averaging forecasts of several individual models (Fried and Yuen 1987). Forecast averaging has been shown to increase the precision of forecasts through the simple process canceling random errors (Clemen 1989), but there is little guidance on selecting the appropriate sets of models to include in the procedure. Bates and Granger (1969) found that averaging was most effective when the errors in the component models were uncorrelated. This is because little cancellation of random observation errors will occur when they are highly positively correlated; the component data series will have errors with similar direction and magnitude. Using the same logic, Ridley (1999) suggested that negatively correlated time series would work best for forecast averaging to increase the precision of forecasts. Based on these observations, we generated a time series of forecasting errors for each of the seven individual forecasting models above, estimated the correlation among them, and then selected the two models with the lowest correlation in forecast errors for use in a forecast-averaging model. As shown later, the two models with lowest correlation were the KF model and the R(yr-2) model ($r = 0.5$). This pair was therefore chosen to be our forecast-averaging model and is referred to as KF + R(yr-2).

Retrospective analysis.—We utilized retrospective analysis to evaluate the performance of the eight forecasting models. Only the data that would have been available to make a forecast for some past year were used for estimating model parameters and generating the forecast. For example, to make a forecast of adult pink salmon in 1980, only data up through brood year 1977 (i.e., adult returns in 1979) were used to estimate model parameters. By iteratively stepping forward through time, that is, sequentially adding a year to the estimation data set, generating a forecast, and comparing the forecast with the observed value, our retrospective analysis produced a time series of forecasting errors for each model. This method thus produces ''out-of-sample'' forecasts, thereby providing a rigorous assessment of each forecasting model's performance if it had been used historically.

We initialized each of the eight forecasting models with data from the first 10 brood years for each stock. After accounting for the data needed for model initialization, the number of years available for forecasting individual stocks ranged from 7 to 37 years, with an average of 18 years across the 43 pink salmon stocks in the northeastern Pacific (Appendix 1). Altogether, each model was evaluated over a period of 783 stock-years.

Performance measures.—We used four performance measures to characterize the central tendency and variability in the distribution of annual forecasting errors: mean raw error (MRE), mean absolute error (MAE), mean percent error (MPE), and root mean square error (RMSE). Each of these performance measures has been used in the past to evaluate forecasting models for Pacific salmon by characterizing the differences between the forecasted ($\hat{R}_t$) and observed (R_t) number of recruits in year t. The raw error, e_i, was calculated as

$$e_i = \hat{R}_t - R_t. \tag{10}$$

Positive values for the raw errors represent forecasts that are too high, whereas negative values represent forecasts that are too low. To obtain the MRE, the raw errors were averaged over the number of years (n) that were forecasted within each stock. This MRE thus reflects the overall bias of the forecasts, and a value of zero is the most desirable. However, large overestimates in some years can be offset to some extent by large underestimates in others, which would tend to produce an MRE close to zero. Thus, to reflect the magnitude of the forecasting errors encountered each year, we calculated the MAE using the absolute value of the raw errors, namely, $\Sigma\ |e_i|/n$. We also calculated the traditional RMSE:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (e_i)^2}{n}}. \tag{11}$$

The RMSE provides a measure of the forecast error variance and can be used to construct confidence intervals for the forecasts. The model that produces the lowest RMSE would also produce the narrowest confidence intervals. The overall (i.e., across the 43 pink salmon stocks and all years) MRE, MAE, and RMSE were not calculated, because the results would have been dominated by the stocks with the highest abundance. Therefore, to evaluate model performance across all stocks and years, we calculated the percent error for each annual forecast of recruits:

$$\text{Percent error} = \left(\frac{\hat{R}_t - R_t}{R_t}\right) \times 100; \tag{12}$$

the mean percent error (MPE) was then calculated by averaging the percent errors from equation (12) over the number of years that were forecast within each stock. The percent error gives equal weighting to both high- and low-abundance stocks, so we also calculated an overall MPE across stocks for each model. However, it should be noted that for the MPE, as well as all the other performance measures, more weight is given to stocks that have longer time series by putting equal weight on each stock-year.

For each stock and performance measure, we ranked the forecasting models from 1 (best) to 8 (worst) based on the absolute value of the results for MRE, MAE, MPE, and RMSE. We also calculated several other similar performance measures, including the mean absolute percent error and median versions of the measures that used means to reflect central tendency, but the rankings for each of these alternative performance measures was highly correlated ($r > 0.6$) with at least one of our four main measures. We therefore describe results using only the above four indicators.

We also calculated for each stock the coefficient of determination (r^2) of the forecasted versus observed returns for the highest-ranking model based on RMSE. The r^2 represents the proportion of the variability in recruitment explained by the best forecasting model. By reporting these values for the highest-ranked models, we provide an upper-bound for the proportion of variance that can be explained in retrospective analyses among our suite of forecasting models.

Results

We found large positive correlations in the raw errors among the seven individual models across all pink salmon stocks and years (Table 2). Correlations were especially high among the stock–recruitment-type models; all were 0.78 or more, and the average was 0.88. The two models with the lowest correlation were the KF model and the R(yr-2) model ($r = 0.5$); they thus composed our forecast-averaging model.

As mentioned in Methods, there were no significant differences in productivity between even- and odd-year lines for the majority of the stocks examined. Furthermore, when we estimated separate cycle line productivities and incorporated them into the retrospective forecasts for the Ricker model, we found that RMSE increased by 31% on

TABLE 2.—Correlations among the annual raw errors of eight forecasting models for 43 pink salmon stocks. The models are defined in the text.

Model	R(yr-2)	2-yr avg.	Ricker	Ricker SST	Ricker AR(1)	ME	KF
2-yr avg.	0.88						
Ricker	0.73	0.85					
Ricker SST	0.71	0.83	0.95				
Ricker AR(1)	0.61	0.76	0.95	0.90			
ME	0.68	0.80	0.87	0.90	0.81		
KF	0.50	0.72	0.88	0.83	0.89	0.78	
KF + R(yr-2)	0.88	0.93	0.92	0.88	0.86	0.84	0.85

average over the Ricker model with one productivity parameter estimate for both cycle lines. This decrease in forecasting ability may be due to imprecision in the productivity estimates caused by smaller sample sizes or could reflect a general lack of evidence for differences in cycle line productivity.

Using our only scale-independent performance measure that could average results across the 43 pink salmon stocks (MPE), we found that the naïve (R[yr-2] and 2-year average) models had the lowest values (82% and 103%; Figure 1). The KF model had the highest overall MPE (268%). The ME model had the lowest overall MPE (197%) of the stock–recruitment-type models (Figure 1). The KF + R(yr-2) forecast-averaging model had an overall MPE of 175%, slightly lower than that of the ME model but more than double that of the R(yr-2) model.

In general, the naïve models demonstrated the best performance, but they did not do so for all stocks. For each performance measure, we tallied the number of stocks (out of the 43 examined) for which each model ranked first (Figures 2–5). The R(yr-2) model ranked first for 49% and 65% of the stocks based on MRE and MPE, respectively (Figures 2, 4), but other models ranked first in the remaining stocks. Similarly, the two naïve models were collectively ranked first most frequently based on MAE and RMSE (Figures 3, 5), but in about 52% of the stocks, other models were the top-ranked ones. For instance, among the stock–recruitment models evaluated, the multistock, mixed effects (ME) model was consistently ranked first more frequently than the others across all four performance measures (Figures 2–5). Furthermore, that ME model was the best for as many stocks as the naïve R(yr-2) model based on mean absolute error (Figure 3).

Thus, no single forecasting model was best for all 43 pink salmon stocks; the best model depended on the particular stock and the performance measure used to evaluate it. For example, each of the eight forecasting models was ranked first for at

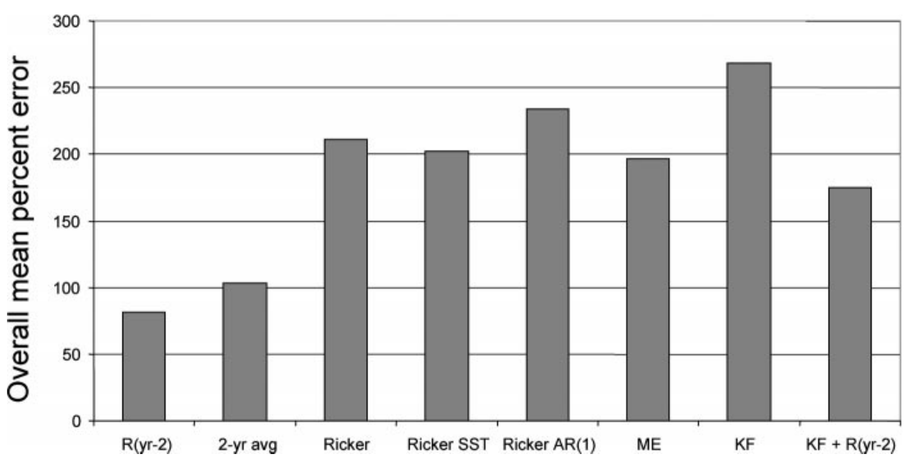

FIGURE 1.—Overall mean percent error in forecasts of the abundance of adult recruits of pink salmon averaged across all 43 pink salmon stocks and all forecasted years for the eight forecasting models (see text for model descriptions).

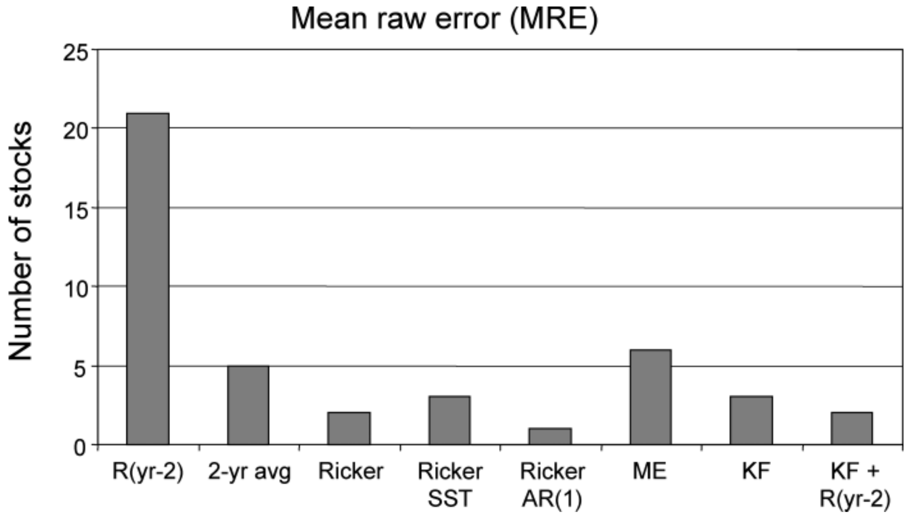

FIGURE 2.—Number of pink salmon stocks (out of a total of 43 stocks) for which each forecasting model is ranked first among the eight models based on mean raw error.

least one stock based on the MRE, MAE, and RMSE performance measures (Figures 2, 3, 5). Only the KF and KF + R(yr-2) models failed to rank first in least one stock based on the MPE performance measure (Figure 4).

The rankings of the eight models for a given stock often depended on which performance measure was used to evaluate them. For example, for the Snohomish (Washington) stock, the R(yr-2) model was ranked first based on the MPE performance measure but eighth based on the RMSE performance measure (Appendix 1). The relatively new forecasting models investigated here, the mixed-effects and Kalman filter models, were the best for only 4 stocks based on the MPE performance measure, but were the best for 9 stocks based on RMSE and for 11 stocks based on MAE.

Although the best models varied to some extent among stocks and performance measures, there was at least some consistency in that certain models were best for certain stocks. For instance, one or the other of the new forecasting models (ME and KF) was best across all four performance measures for the Nooksack, Washington, pink salmon

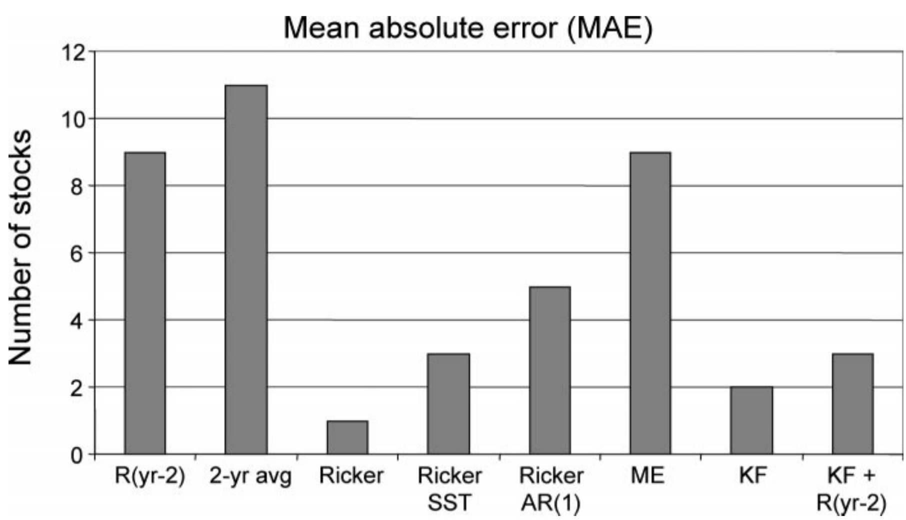

FIGURE 3.—Number of pink salmon stocks for which each forecasting model is ranked first among the eight models based on mean absolute error.

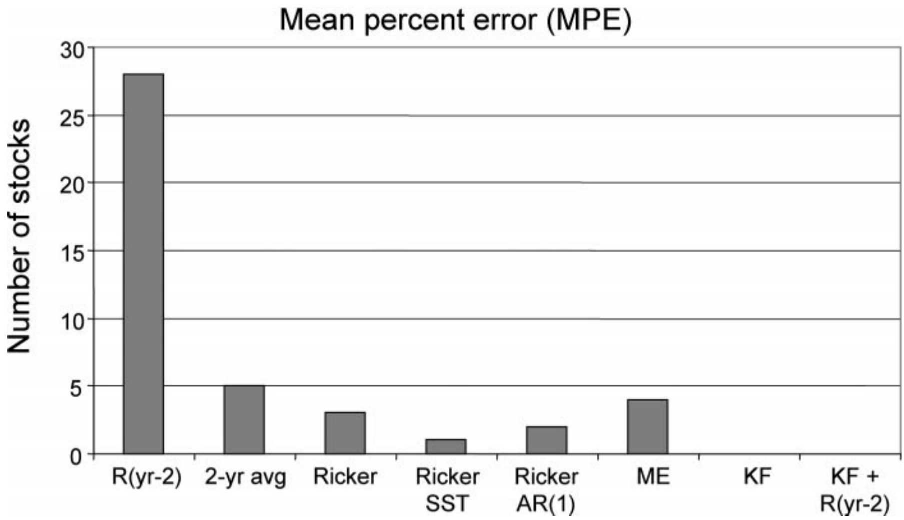

FIGURE 4.—Number of pink salmon stocks for which each forecasting model is ranked first among the eight models based on mean percent error.

stock and across three of the four measures for four other stocks (Skagit, Washington; Eastern District of Prince William Sound; Southwest and Unimak District for the Alaska Peninsula; and Norton Sound–Moses Point, Alaska; Appendix 1). For the Golovin, Alaska, stock, the Ricker model with summer sea surface temperature as an explanatory variable was consistently the top-ranked model across all four performance measures (Appendix 1). In 15 stocks, one or the other of the naïve models was best across all four performance measures (Appendix 1).

In general, the four different performance measures reflected somewhat different characteristics of the forecasting errors as indicated by the rankings given to the models. The rankings of models based on MRE were only moderately correlated with the rankings based on the other three performance measures (*r* ranged from 0.37 to 0.43). The same was true for MPE (*r* ranged from 0.41 to

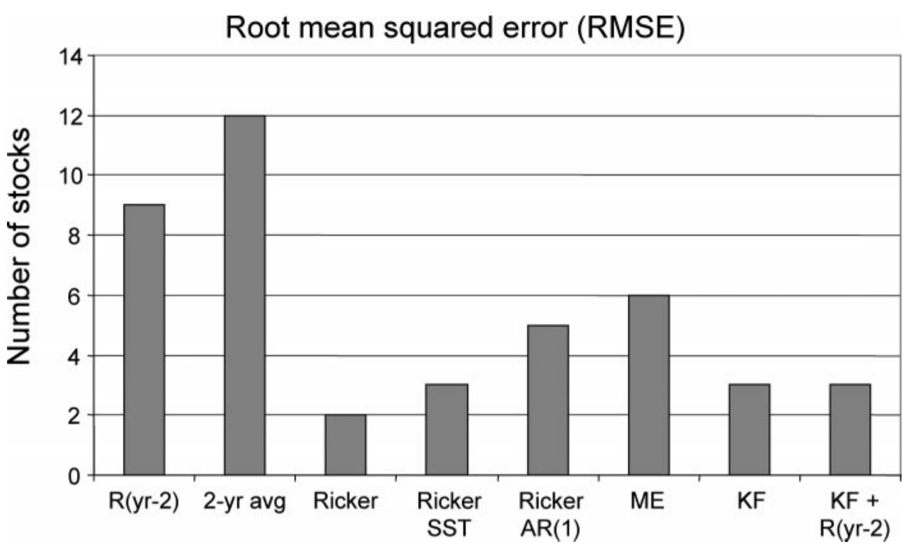

FIGURE 5.—Number of pink salmon stocks for which each forecasting model is ranked first among the eight models, based on root mean square error.

0.55), but the rankings based on MAE and RMSE were quite similar (r = 0.84). To remove the potential effect of large outliers in forecasts, we also calculated median rather than mean performance measures, but the rankings of the models and the conclusions changed very little. We also developed a performance measure that averaged the five largest absolute errors for each stock to examine which models best avoided large errors. However, we found that the ranking based on this performance measure was highly correlated with the ranking based on RMSE (r = 0.91). Therefore, the rankings based on RMSE are sufficient to indicate which models avoid unusually large errors.

As with the seven individual models, the relative performance of the forecast-averaging model depended on the stock and the performance measure used for ranking (Figures 2–5). The model had a higher ranking and a smaller forecasting error than both of its component models in 40 out of 172 cases (23%) across the four performance measures and 43 stocks. Using RMSE, it was better than both of its component models for 20 out of 43 stocks (47%).

Another measure of a forecasting model's usefulness is its average rank across the 43 stocks for a given performance measure (Figure 6). Figures 2–5 only indicated the frequency with which a model was ranked number 1; however, certain models were ranked highly for some stocks and poorly for others (giving only a mediocre average ranking), whereas other models were consistently ranked near the top. The forecast-averaging model is an example of the latter. It was among the top three models for 22 of 43 stocks based on RMSE even though it was top-ranked in only a few stocks (Figures 2–5).

Despite our examining a wide range of forecasting models, generally only a small proportion of the variability in recruitment was explained by the highest-ranked model (e.g., Figure 7 based on RMSE). The r^2 values for the individual stocks ranged from 0.001 to 0.8. The average r^2 across the 43 stocks was 0.2. The best model for each stock generally explained a higher proportion of the variation in recruitment for Alaskan pink salmon stocks than for those in Washington and British Columbia; 11 of the 14 Washington and British Columbia stocks (numbered 1−14 in Figure 7 and Table 1) had below-average r^2 values, whereas 17 of the remaining 29 Alaskan stocks had above-average values. These r^2 values correspond to forecasts of the abundance of recruits and should not be compared with r^2 values from models that forecast $\log_e$ transformed abundance (e.g., Wood et al. 1997) because the dependent variable is different. The latter is more likely to produce higher r^2 values, but we chose the former because abundance is the unit that managers and those in the industry use on a daily basis.

Discussion

Because many salmon forecasting models tend to perform poorly, we conducted a comprehensive comparison of some newly developed models and several existing models representing a wide range of categories. These models had an extensive variety of complexities, realism, and data requirements. Furthermore, because many salmon forecasting models have been developed for particular stocks using data from only a specific period, we used a single, large data set that included 43 pink salmon stocks with spawning areas and points of ocean entry ranging widely along the northeastern Pacific coast of North America. We evaluated the performance of the models over 783 stock-years.

Our results were consistent with those of past studies that compared forecasting models for Pacific salmon (Fried and Yuen 1987; Noakes et al. 1990; Wood et al. 1997; Adkison 2002; Zhou 2003); no one model emerged as being consistently superior for these pink salmon stocks. Which model was best was highly dependent on both the stock and the performance measure. We were surprised by the generally good performance of the naïve models. Even though they did not explicitly account for biological or environmental processes (e.g., spawner abundance), the naïve models demonstrated an overall MPE roughly one-half that of the next best model. This general difference between the naïve and complex models may be due to (1) the greater number of parameters to estimate in the complex models (which creates more chances for the errors in those estimates to degrade forecasts), (2) the greater number of explanatory variables used in the complex models (which similarly creates more chances for the errors in the data for those variables to corrupt the forecasts), (3) our lack of understanding of the critical processes governing the survival of salmon to recruitment (which leads to misspecification of the model), (4) the assumed error structures (additive and normal for the naïve models versus multiplicative and lognormal for the stock–recruitment models), or (5) a combination of these factors. For the pink salmon examined here, we cannot attribute the relatively poor performance of the stock–recruitment models to uncertainty in age at return

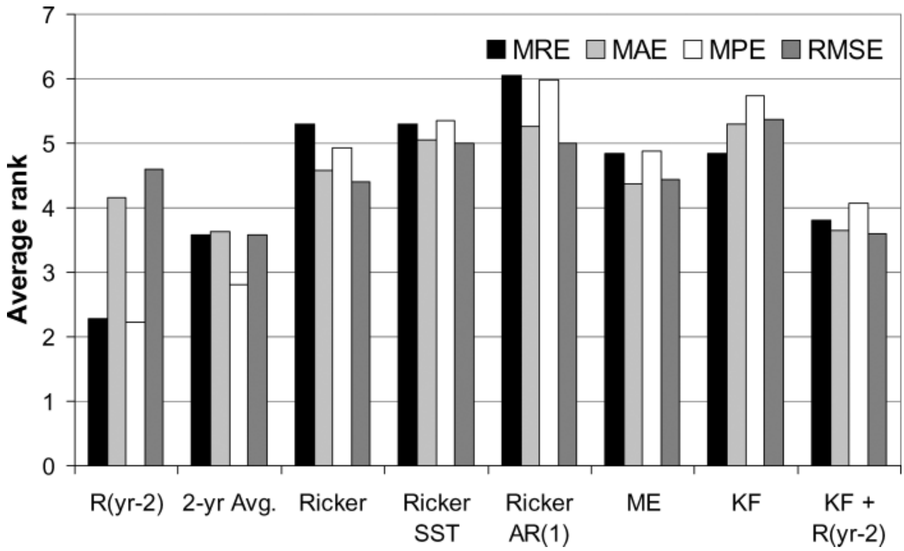

FIGURE 6.—Average rank of the eight forecasting models across the 43 pink salmon stocks for each performance measure. A rank of 1 is the best. Performance measures are as follows: MRE = mean raw error, MAE = mean absolute error, MPE = mean percent error, and RMSE = root mean square error.

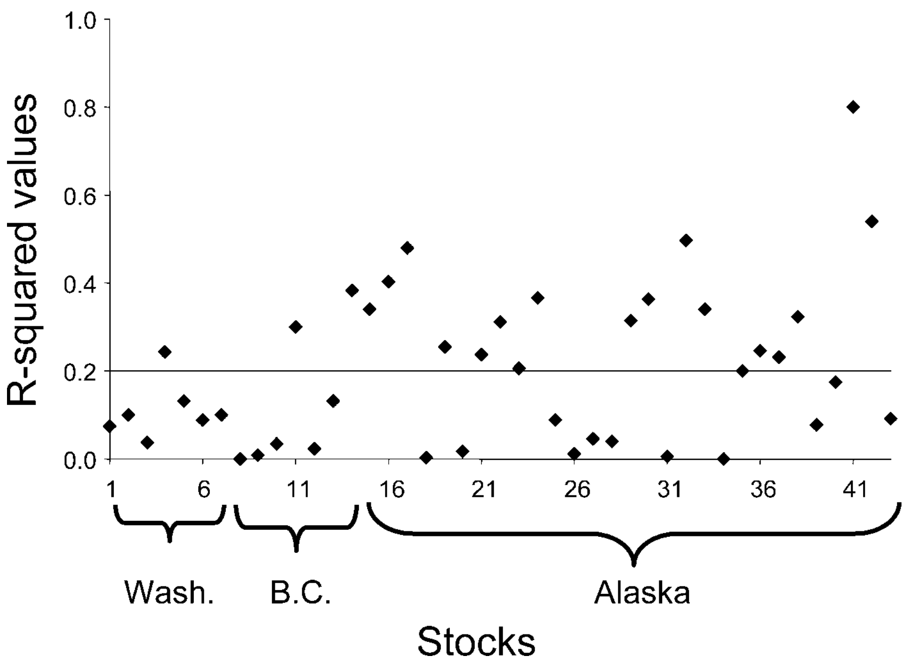

FIGURE 7.—Proportion of the temporal variation in recruitment explained by the highest-ranked forecasting model for each pink salmon stock based on root mean square error (RMSE). Symbols represent the r^2 values for the models with the lowest RMSE for each stock. The solid line denotes the average r^2 value across the 43 stocks. Stock numbers (x-axis) are arranged geographically from Washington State (Wash.) in the south (stock 1) to Norton Sound in Western Alaska (stocks 40–43); B.C. = British Columbia. See Table 1 for additional information on these stocks.

(as suggested by Wood et al. 1997 for sockeye salmon *O. nerka* and chum salmon *O. keta*) because all pink salmon mature at age 2.

Nevertheless, one of the newer and more complicated models, the multistock, mixed effects model, performed well compared with the naïve and other models according to the MAE criterion. This measure is directly relevant to both fisheries managers and the fishing industry because, unlike the MRE, which reflects the average bias over the long term, the MAE reflects precision, that is, the average magnitude of forecasting error in each year. Costs related to the magnitude of over- or underestimation of recruits are incurred each year (in terms of lost revenue from harvesting and too much or too little escapement). Therefore, the relatively good performance of the ME model in 21% of the stocks suggests that salmon forecasters should consider this model when evaluating alternatives for preseason forecasting of pink salmon recruitment along the West Coast of North America.

Regardless of which model is deemed best, substantial unexplained variability in pink salmon recruitment remains for most stocks and the mean percent error of forecasts is large (in the 80–100% range for the best models). As this result occurs across a wide range of models, it is difficult to envision how further improvements in estimation procedures or revisions to models will substantially improve forecasts of pink salmon recruitment. The correction for the prediction bias described in Chen (2004) may improve forecasts somewhat, but only by a few percentage points. Forecasts are likely to remain poor unless pink salmon monitoring programs are altered to use some new, highly significant covariate, such as the abundance of fry leaving freshwater or the abundance of juveniles at sea (Adkison 2002). For the stock–recruitment models, small improvements in accuracy may be possible with more precise estimates of spawner escapement. Increasing model complexity or sophistication does not appear to be a solution. It is therefore incumbent on both management agencies and the fishing industry to take a precautionary approach to their actions on pink salmon (FAO 1995a, 1995b). This means, among other things, explicitly taking into account the large uncertainties in forecasts of abundance (and other components of a fishery system) when evaluating options for fishing regulations, especially early in a fishing season. Through risk assessments and decision analyses that consider such uncertainties, it is possible to determine the most appropriate level of adjustment to an early-season fishing plan or to a target escapement (e.g., Frederick and Peterman 1995; Robb and Peterman 1998).

Our approach was to extensively evaluate a broad suite of generally applicable models, but we found that none is universally appropriate. Nonetheless, an intensive exploration and development of models for an individual stock may result in improved forecasts. For instance, Shotwell et al. (in press) conducted a comprehensive study of individual Western Alaska chum salmon stocks that identified environmental variables that significantly improved forecasts of the $\log_e$ transformed number of recruits. Such an exhaustive search for other stocks may reveal environmental variables, such as stream flows or early ocean conditions, that could be useful in forecasting returns (Adkison et al. 1996). However, we should remember that although certain models may offer promise initially, those models often do not work well when new data are used to judge their performance (Myers 1998).

The Kalman filter model (equations 7 and 8) has demonstrated promise in simulation studies that examine changing productivity regimes (Peterman et al. 2000). Despite that success, in the current analysis the KF model did not perform as well overall as the standard Ricker model. This weak performance may be due to the lack of substantial changes in underlying productivity over time in pink salmon (as opposed to year-to-year variation). Large changes tend to create a situation in which the KF model is most beneficial (Peterman et al. 2000). However, in our examination of the time series of a_t from the Kalman filter estimation, we generally did not see evidence of systematic underlying changes in the Ricker a parameter over time for pink salmon. This observation is consistent with previous results for this species (Pyper et al. 2002).

Like the findings of Fried and Yuen (1987) and Noakes et al. (1990) with sockeye salmon, our results suggest that forecast averaging may improve precision in some cases. When forecast averaging has been used in salmon forecasting, the component models have usually been stock–recruitment models (using the abundance of adults or smolts as the independent variable) and sibling models (using the abundance of other-aged adults from the same cohort, which is not applicable to pink salmon). However, we found high positive correlation in the errors among the different stock–recruitment models, suggesting that those models are accounting for—and missing—the same time-varying events. Because of the qualitatively different nature of the R(yr-2) and KF models and the relatively low correlation among their forecast errors, combining their forecasts made intuitive sense here. Our forecast-averaging model had a lower RMSE than either of the component models for 47% of the stocks evaluated but was ranked first of all eight models for only three of those stocks. Determining exactly which forecasts should be averaged to improve precision or accuracy is a difficult task. Other combinations may or may not have been fruitful, although we examined others without finding any with improved performance. Given the high correlation in the raw errors among stock–recruitment models, we expect that they would not be good candidates as components of the forecast-averaging model because the chance of error cancellation is low.

Although the long time series used in this analysis allowed for a robust evaluation of forecasting models, changes in the methods used to estimate abundance may have occurred over time. Switching assessment methods (e.g., from weir counts to aerial surveys) or procedures for calculating abundance (e.g., expansion factors that convert population abundance indices to abundance estimates) could have affected the time series that were used as data inputs. We have assumed that the biologists involved in assessing each stock used their best professional judgment to maintain the comparability of data in cases where changes occurred in assessment methods. The effects of potential changes in data quality over time on the performance of forecasting models are unknown.

The choice of the most appropriate forecasting model for the abundance of salmon recruits is not a simple one because salmon forecasters hold various opinions about which performance measures best capture the most relevant aspects of the distributions of forecasting errors. For this reason, we provide an Appendix summarizing the ranked performance for each model across all stocks and performance measures. That table allows readers to weight the performance measures appropriately. In addition, both fisheries managers and people in the fishing and processing sectors consider many other issues besides the accuracy of a forecasting model. For instance, in salmon fisheries, overestimates of recruitment by preseason forecasts typically tend to result in more catch than is desirable and fewer spawners than the target, whereas underestimates of recruitment tend to lead to reduced catches and more spawners than the target (e.g., Bocking and Peterman 1988). Loss functions (Reckhow 1994; Frederick and Peterman 1995; Chatfield 2000) can quantify the various types of costs and risks associated with various magnitudes and directions of forecasting errors (Bocking and Peterman 1988), and these could be incorporated into performance measures to rank alternative forecasting models. Unfortunately, little work has been done on loss functions for Pacific salmon. At present, the most commonly used performance measures, such as MRE, MAE, MPE, and RMSE, implicitly assume a linear, symmetric loss function in which forecasting errors of a given magnitude in one direction are as undesirable as the same forecasting error in the opposite direction. Using a different approach that reflects what are actually nonlinear and asymmetric loss functions would probably produce different rankings of the models than those shown here. We are currently developing decision analyses taking this approach.

Despite the extensive analyses reported here, it is conceivable that the model that performs best retrospectively for a given stock or group of stocks may not be the best model for forecasting in the future. This could be the situation if, for instance, the relatively limited sample of variations during the historical period covered by our data on catch, abundance of spawners, environmental processes, and measurement errors does not sufficiently represent the range and variation in those variables that will occur in the future. In other words, the ranking of models reported here may have been influenced by the particular sequence of historical events covered by our data set. This is why we also need to do prospective (not retrospective) analyses using Monte Carlo simulations, in which the performance of each model is tested in thousands of scenarios, each reflecting a different sequence of future stochastic events rather than just the one scenario of events observed historically for each stock. We are currently conducting such simulations using a variation on the climate model reported in Peterman et al. (2000).

Acknowledgments

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Appendix follows

Appendix: Performance Measures and Rankings

TABLE A.1.—Summary of performance measures and rankings (in parentheses) of eight models for forecasting pink salmon recruitment. Each of the 43 stocks studied is listed by region; *n* is the number of years that were forecasted after the initial 10 brood years of data were used to initialize each model. Performance measures are as follows: MRE = mean root error, MAE = mean absolute error, MPE = mean percent error, and RMSE = root mean square error; see text for model descriptions.

Region	Stock or District	*n*	Model	MRE	MAE	MPE	RMSE
Washington	Nooksack	9	R(yr-2)	22,505 (6)	121,554 (8)	69 (7)	147,676 (8)
			2-yr avg.	9,476 (2)	103,763 (7)	54 (4)	122,451 (7)
			Ricker	18,544 (5)	75,850 (3)	53 (3)	90,853 (2)
			Ricker SST	60,142 (8)	96,793 (6)	90 (8)	113,660 (6)
			Ricker AR(1)	23,770 (7)	78,350 (4)	58 (6)	93,800 (3)
			ME	−7,249 (1)	75,178 (2)	37 (1)	101,004 (4)
			KF	9,631 (3)	68,739 (1)	45 (2)	87,062 (1)
			KF + R(yr-2)	16,068 (4)	69,724 (5)	57 (5)	106,751 (5)
	Skagit	9	R(yr-2)	97,054 (3)	560,760 (8)	160 (8)	695,275 (8)
			2-yr avg.	60,661 (1)	501,981 (7)	121 (3)	605,249 (7)
			Ricker	193,322 (7)	376,612 (3)	123 (4)	479,101 (2)
			Ricker SST	178,619 (6)	392,675 (5)	126 (5)	499,872 (5)
			Ricker AR(1)	229,925 (8)	377,631 (4)	130 (6)	497,740 (4)
			ME	83,292 (2)	368,928 (1)	106 (1)	485,066 (3)
			KF	154,419 (5)	375,799 (2)	117 (2)	461,684 (1)
			KF + R(yr-2)	125,737 (4)	453,127 (5)	139 (7)	566,139 (6)
	Stillaguamish	9	R(yr-2)	18,921 (2)	151,024 (3)	81 (2)	163,216 (2)
			2-yr avg.	9,388 (1)	107,423 (1)	53 (1)	127,514 (1)
			Ricker	223,906 (6)	239,713 (6)	242 (5)	276,261 (5)
			Ricker SST	346,041 (8)	357,270 (8)	400 (8)	431,236 (8)
			Ricker AR(1)	248,072 (7)	261,977 (7)	264 (7)	300,619 (7)
			ME	222,634 (5)	234,654 (5)	251 (6)	283,743 (6)
			KF	197,666 (4)	217,798 (4)	219 (4)	252,716 (4)
			KF + R(yr-2)	108,294 (3)	148,738 (2)	150 (3)	186,588 (3)
	Snohomish	9	R(yr-2)	27,071 (1)	127,148 (4)	31 (1)	168,530 (8)
			2-yr avg.	33,435 (2)	106,949 (2)	37 (2)	146,642 (3)
			Ricker	79,294 (6)	134,833 (6)	75 (7)	157,189 (5)
			Ricker SST	84,761 (7)	138,368 (7)	73 (6)	159,249 (6)
			Ricker AR(1)	87,792 (8)	141,227 (8)	79 (8)	161,199 (7)
			ME	45,016 (3)	100,906 (1)	47 (3)	123,208 (1)
			KF	72,471 (5)	127,685 (5)	71 (5)	152,357 (4)
			KF + R(yr-2)	49,771 (4)	118,798 (3)	51 (4)	146,540 (2)
	Puyallup River	9	R(yr-2)	11,054 (3)	34,081 (7)	147 (1)	44,161 (8)
			2-yr avg.	12,710 (7)	34,098 (8)	152 (2)	39,322 (7)
			Ricker	12,681 (6)	27,803 (4)	265 (7)	34,378 (4)
			Ricker SST	7,132 (2)	24,440 (2)	187 (4)	31,370 (2)
			Ricker AR(1)	13,425 (8)	28,101 (5)	270 (8)	34,714 (5)
			ME	4,305 (1)	21,582 (1)	165 (3)	27,584 (1)
			KF	11,786 (5)	27,106 (3)	255 (6)	33,259 (3)
			KF + R(yr-2)	11,420 (4)	29,132 (6)	201 (5)	35,305 (6)
	Hood Canal	9	R(yr-2)	6,375 (1)	41,692 (1)	106 (1)	52,166 (1)
			2-yr avg.	8,729 (2)	46,383 (2)	129 (2)	53,722 (2)
			Ricker	124,116 (6)	124,116 (6)	499 (5)	148,650 (5)
			Ricker SST	114,032 (5)	114,032 (5)	503 (6)	151,147 (6)
			Ricker AR(1)	137,817 (7)	137,817 (7)	547 (7)	162,751 (7)
			ME	151,524 (8)	151,524 (8)	588 (8)	176,696 (8)
			KF	105,623 (4)	107,830 (4)	415 (4)	133,957 (4)
			KF + R(yr-2)	55,999 (3)	64,544 (3)	261 (3)	85,331 (3)
	Dungeness	9	R(yr-2)	18,014 (1)	25,831 (1)	344 (1)	56,679 (2)
			2-yr avg.	21,655 (2)	30,358 (3)	399 (2)	49,595 (1)
			Ricker	33,872 (6)	38,211 (5)	550 (5)	66,592 (5)
			Ricker SST	33,233 (5)	39,139 (6)	550 (6)	79,275 (7)
			Ricker AR(1)	37,263 (7)	41,394 (7)	598 (7)	72,180 (6)
			ME	42,266 (8)	46,209 (8)	665 (8)	80,399 (8)
			KF	30,760 (4)	35,475 (4)	506 (4)	61,312 (4)
			KF + R(yr-2)	24,387 (3)	29,753 (2)	425 (3)	58,543 (3)

TABLE A.1.—Continued.

Region	Stock or District	*n*	Model	MRE	MAE	MPE	RMSE
Fraser River	Total	10	R(yr-2)	30,000 (1)	5,990,000 (2)	14 (2)	6,488,220 (1)
			2-yr avg.	−360,000 (2)	5,950,000 (1)	13 (1)	6,832,276 (2)
			Ricker	2,038,254 (5)	7,937,085 (6)	38 (5)	9,555,152 (6)
			Ricker SST	2,941,418 (7)	8,968,758 (8)	46 (8)	10,529,166 (8)
			Ricker AR(1)	2,333,472 (6)	8,061,423 (7)	40 (6)	9,683,253 (7)
			ME	3,036,959 (8)	7,910,360 (5)	43 (7)	9,262,495 (5)
			KF	1,037,458 (4)	7,275,731 (4)	31 (4)	8,777,956 (4)
			KF + R(yr-2)	533,729 (3)	6,263,595 (3)	23 (3)	7,303,512 (3)
Mainland British Columbia	Statistical Areas 12, 13, 15, 16	11	R(yr-2)	8,491 (2)	1,922,539 (5)	36 (1)	2,371,431 (2)
			2-yr avg.	1,851 (1)	1,995,594 (7)	57 (2)	2,429,920 (4)
			Ricker	585,863 (5)	1,895,583 (3)	104 (6)	2,426,761 (3)
			Ricker SST	557,523 (4)	2,071,316 (8)	108 (8)	2,724,508 (8)
			Ricker AR(1)	650,695 (8)	1,921,643 (4)	108 (7)	2,455,579 (5)
			ME	595,323 (7)	1,816,904 (1)	95 (4)	2,545,835 (7)
			KF	591,166 (6)	1,967,743 (6)	100 (5)	2,475,099 (6)
			KF + R(yr-2)	299,839 (3)	1,822,648 (2)	68 (3)	2,272,220 (1)
Central British Columbia	Statistical Area 10	36	R(yr-2)	1,968 (1)	28,493 (2)	158 (1)	44,821 (2)
			2-yr avg.	2,564 (2)	27,993 (1)	163 (2)	40,405 (1)
			Ricker	20,265 (5)	39,573 (5)	392 (6)	48,517 (4)
			Ricker SST	17,139 (3)	37,774 (3)	370 (4)	46,864 (3)
			Ricker AR(1)	21,535 (6)	40,041 (6)	399 (7)	48,908 (5)
			ME	17,310 (4)	38,167 (4)	347 (3)	50,010 (6)
			KF	50,657 (8)	66,085 (8)	620 (8)	79,899 (8)
			KF + R(yr-2)	26,313 (7)	43,103 (7)	389 (5)	52,159 (7)
	Statistical Area 9	37	R(yr-2)	−1,340 (1)	240,854 (2)	51 (1)	397,039 (2)
			2-yr avg.	−3,002 (2)	182,695 (1)	85 (2)	298,604 (1)
			Ricker	313,324 (5)	512,907 (5)	440 (5)	610,648 (4)
			Ricker SST	280,584 (4)	460,746 (4)	253 (3)	725,259 (6)
			Ricker AR(1)	349,131 (6)	554,996 (6)	462 (6)	655,989 (5)
			ME	238,397 (3)	410,110 (3)	283 (4)	572,424 (3)
			KF	1,591,368 (8)	1,711,207 (8)	1,069 (8)	2,873,922 (8)
			KF + R(yr-2)	795,014 (7)	900,451 (7)	560 (7)	1,481,451 (7)
	Statistical Area 8	37	R(yr-2)	82,123 (2)	2,397,553 (3)	85 (1)	3,989,920 (6)
			2-yr avg.	68,311 (1)	2,467,270 (5)	144 (2)	3,844,000 (4)
			Ricker	572,173 (6)	2,520,765 (7)	175 (6)	4,199,098 (8)
			Ricker SST	405,323 (5)	2,488,442 (6)	165 (4)	3,952,861 (5)
			Ricker AR(1)	307,842 (4)	2,312,075 (2)	168 (5)	3,810,961 (3)
			ME	154,427 (3)	2,193,931 (1)	177 (7)	3,667,294 (1)
			KF	1,065,130 (8)	2,724,659 (8)	218 (8)	4,173,200 (7)
			KF + R(yr-2)	573,627 (7)	2,425,412 (4)	151 (3)	3,807,202 (2)
Northern British Columbia	Statistical Area 6	36	R(yr-2)	33,981 (2)	1,560,281 (4)	64 (1)	2,257,228 (6)
			2-yr avg.	46,492 (3)	1,667,677 (7)	99 (2)	2,320,879 (7)
			Ricker	213,676 (5)	1,622,569 (5)	150 (6)	2,089,932 (4)
			Ricker SST	33,875 (1)	1,532,157 (2)	128 (3)	2,022,807 (2)
			Ricker AR(1)	232,024 (6)	1,632,167 (6)	155 (7)	2,120,716 (5)
			ME	98,282 (4)	1,489,211 (1)	136 (5)	2,015,141 (1)
			KF	769,833 (8)	1,906,188 (8)	206 (8)	2,325,902 (8)
			KF + R(yr-2)	401,907 (7)	1,555,497 (3)	135 (4)	2,080,916 (3)
	Statistical Area 2E	36	R(yr-2)	−132 (1)	299,337 (2)	56 (1)	524,361 (6)
			2-yr avg.	3,948 (2)	266,798 (1)	64 (2)	457,816 (1)
			Ricker	109,823 (7)	326,173 (3)	181 (5)	479,848 (4)
			Ricker SST	102,054 (5)	411,132 (8)	173 (4)	599,463 (8)
			Ricker AR(1)	27,107 (3)	346,075 (6)	301 (8)	472,903 (2)
			ME	60,320 (4)	339,973 (5)	223 (6)	478,827 (3)
			KF	216,673 (8)	386,706 (7)	234 (7)	574,460 (7)
			KF + R(yr-2)	108,271 (6)	334,710 (4)	145 (3)	523,676 (5)

TABLE A.1.—Continued.

Region	Stock or District	n	Model	MRE	MAE	MPE	RMSE
Southeast Alaska	Southern (Districts 101–108)	27	R(yr-2)	−3,099,202 (2)	17,786,351 (8)	12 (7)	25,140,233 (8)
			2-yr avg.	−5,720,618 (4)	15,066,870 (2)	3 (2)	22,031,466 (6)
			Ricker	−8,132,745 (7)	16,620,489 (6)	5 (3)	21,730,578 (5)
			Ricker SST	−7,190,360 (6)	16,446,106 (5)	8 (5)	21,140,091 (2)
			Ricker AR(1)	−9,837,480 (8)	17,252,227 (7)	0 (1)	23,069,089 (7)
			ME	−2,319,315 (1)	15,654,968 (3)	26 (8)	21,490,794 (3)
			KF	−6,728,668 (5)	16,444,275 (4)	5 (4)	21,697,825 (4)
			KF + R(yr-2)	−4,913,935 (3)	14,855,991 (1)	9 (6)	19,975,629 (1)
	Northern Inside (Districts 109–112, 114, 116)	27	R(yr-2)	−1,159,687 (4)	7,822,353 (8)	18 (1)	10,923,443 (8)
			2-yr avg.	−1,400,977 (5)	7,289,156 (7)	25 (2)	10,357,496 (7)
			Ricker	−2,946,095 (8)	6,587,863 (3)	32 (5)	9,360,207 (4)
			Ricker SST	−2,401,016 (6)	6,784,454 (5)	38 (7)	9,324,849 (3)
			Ricker AR(1)	−2,671,113 (7)	6,057,556 (1)	27 (4)	8,907,055 (1)
			ME	−908,573 (1)	6,561,928 (2)	65 (8)	9,434,231 (5)
			KF	−1,006,048 (2)	7,188,441 (6)	34 (6)	9,944,425 (6)
			KF + R(yr-2)	−1,082,868 (3)	6,623,346 (4)	26 (3)	9,276,054 (2)
	Northern Outside (311)	27	R(yr-2)	−815,900 (4)	1,804,697 (5)	6 (1)	2,783,547 (7)
			2-yr avg.	−996,548 (8)	2,064,942 (8)	6 (2)	2,905,662 (8)
			Ricker	−893,506 (7)	1,795,022 (4)	17 (5)	2,619,538 (3)
			Ricker SST	−736,097 (3)	1,692,653 (2)	16 (4)	2,509,077 (2)
			Ricker AR(1)	−721,411 (2)	1,673,993 (1)	21 (7)	2,496,065 (1)
			ME	−381,019 (1)	1,944,290 (7)	32 (8)	2,630,796 (4)
			KF	−863,975 (6)	1,838,646 (6)	20 (6)	2,646,808 (6)
			KF + R(yr-2)	−839,938 (5)	1,784,286 (3)	13 (3)	2,640,206 (5)
Yakutat	Situk River	15	R(yr-2)	2,205 (1)	230,127 (7)	190 (6)	262,564 (7)
			2-yr avg.	−20,660 (5)	176,717 (4)	127 (5)	211,038 (4)
			Ricker	−19,988 (4)	161,971 (2)	80 (3)	188,722 (2)
			Ricker SST	−4,382 (2)	176,799 (5)	91 (4)	216,379 (5)
			Ricker AR(1)	−17,402 (3)	157,311 (1)	78 (1)	182,741 (1)
			ME	−24,839 (6)	166,602 (3)	80 (2)	207,537 (3)
			KF	207,396 (8)	289,821 (8)	259 (8)	364,819 (8)
			KF + R(yr-2)	104,800 (7)	217,187 (6)	225 (7)	258,726 (6)
	Humpy Creek	12	R(yr-2)	21,591 (1)	77,400 (3)	338 (2)	103,791 (5)
			2-yr avg.	31,667 (2)	50,885 (1)	281 (1)	70,326 (1)
			Ricker	69,147 (5)	89,232 (5)	383 (6)	103,055 (4)
			Ricker SST	75,400 (6)	99,584 (6)	418 (7)	118,751 (6)
			Ricker AR(1)	89,295 (7)	106,554 (7)	354 (5)	127,060 (7)
			ME	96,502 (8)	116,416 (8)	540 (8)	132,109 (8)
			KF	58,011 (4)	79,894 (4)	354 (4)	93,636 (3)
			KF + R(yr-2)	39,801 (3)	65,563 (2)	346 (3)	77,301 (2)
Prince William Sound	Eastern District	20	R(yr-2)	−181,484 (3)	3,377,937 (8)	114 (6)	4,443,969 (7)
			2-yr avg.	−388,927 (4)	3,156,566 (5)	99 (5)	3,666,798 (1)
			Ricker	−753,723 (6)	3,185,434 (7)	86 (3)	4,477,685 (8)
			Ricker SST	−615,527 (5)	2,924,016 (2)	73 (2)	4,055,865 (5)
			Ricker AR(1)	−1,123,130 (8)	3,053,650 (4)	87 (4)	3,805,617 (3)
			ME	−875,519 (7)	2,753,255 (1)	60 (1)	3,717,661 (2)
			KF	−89,102 (1)	3,162,675 (6)	133 (8)	4,318,621 (6)
			KF + R(yr-2)	−135,293 (2)	2,975,607 (3)	124 (7)	3,991,405 (4)
	Montague District	16	R(yr-2)	−11,920 (1)	272,426 (1)	53 (1)	535,715 (7)
			2-yr avg.	31,564 (2)	300,007 (3)	73 (2)	492,332 (4)
			Ricker	120,269 (5)	315,965 (6)	191 (5)	441,184 (3)
			Ricker SST	171,687 (6)	306,696 (4)	160 (4)	407,248 (1)
			Ricker AR(1)	229,082 (7)	405,466 (8)	226 (7)	620,013 (8)
			ME	242,180 (8)	346,820 (7)	209 (6)	432,380 (2)
			KF	90,964 (4)	314,323 (5)	256 (8)	515,774 (6)
			KF + R(yr-2)	39,522 (3)	279,087 (2)	154 (3)	493,332 (5)

TABLE A.1.—Continued.

Region	Stock or District	*n*	Model	MRE	MAE	MPE	RMSE
Prince William Sound	Southeastern District	20	R(yr-2)	16,011 (1)	830,845 (2)	50 (1)	1,238,844 (1)
			2-yr avg.	30,812 (2)	825,556 (1)	83 (2)	1,242,490 (2)
			Ricker	2,109,643 (7)	2,546,364 (7)	377 (7)	5,355,045 (7)
			Ricker SST	1,614,629 (6)	2,098,430 (6)	308 (6)	3,242,158 (5)
			Ricker AR(1)	3,904,749 (8)	4,358,664 (8)	459 (8)	12,166,651 (8)
			ME	1,257,779 (4)	1,746,179 (4)	284 (5)	2,192,232 (3)
			KF	1,489,071 (5)	1,938,848 (5)	251 (4)	4,262,285 (6)
			KF + R(yr-2)	752,541 (3)	1,258,941 (3)	151 (3)	2,493,717 (4)
Lower Cook Inlet	Southern District	27	R(yr-2)	−741 (2)	153,452 (3)	61 (1)	239,116 (6)
			2-yr avg.	−102 (1)	132,380 (1)	61 (2)	203,764 (1)
			Ricker	26,299 (5)	160,766 (5)	131 (5)	224,497 (3)
			Ricker SST	52,067 (7)	184,200 (7)	139 (6)	248,655 (7)
			Ricker AR(1)	43,615 (6)	167,516 (6)	143 (7)	234,943 (5)
			ME	87,208 (8)	203,781 (8)	153 (8)	268,481 (8)
			KF	11,129 (4)	160,243 (4)	109 (4)	229,439 (4)
			KF + R(yr-2)	5,194 (3)	143,428 (2)	85 (3)	219,842 (2)
	Outer District	27	R(yr-2)	756 (1)	290,052 (1)	193 (1)	426,181 (1)
			2-yr avg.	−2,857 (2)	291,643 (2)	332 (7)	479,704 (3)
			Ricker	234,026 (5)	367,338 (4)	329 (5)	517,354 (5)
			Ricker SST	340,594 (7)	460,711 (7)	301 (4)	634,426 (7)
			Ricker AR(1)	303,470 (6)	403,253 (6)	355 (8)	622,667 (6)
			ME	352,841 (8)	461,696 (8)	293 (3)	653,955 (8)
			KF	216,244 (4)	372,568 (5)	329 (6)	501,306 (4)
			KF + R(yr-2)	108,500 (3)	302,672 (3)	261 (2)	439,077 (2)
	Kamishak District	24	R(yr-2)	−10,125 (1)	313,633 (6)	165 (1)	535,692 (7)
			2-yr avg.	−22,390 (2)	302,831 (5)	319 (3)	482,734 (6)
			Ricker	85,497 (5)	275,471 (3)	507 (7)	418,141 (2)
			Ricker SST	192,275 (8)	428,854 (8)	458 (5)	595,767 (8)
			Ricker AR(1)	129,816 (7)	298,504 (4)	611 (8)	429,373 (4)
			ME	107,011 (6)	327,707 (7)	401 (4)	480,388 (5)
			KF	65,518 (4)	263,549 (2)	461 (6)	408,524 (1)
			KF + R(yr-2)	27,696 (3)	261,172 (1)	313 (2)	420,926 (3)
Kodiak Island	Afognak District	7	R(yr-2)	−17,330 (1)	1,443,229 (7)	111 (8)	1,818,142 (8)
			2-yr avg.	−60,589 (2)	1,520,723 (8)	105 (5)	1,801,026 (7)
			Ricker	−463,981 (8)	1,131,994 (2)	60 (1)	1,477,680 (2)
			Ricker SST	−409,944 (5)	1,124,828 (1)	62 (3)	1,468,278 (1)
			Ricker AR(1)	−426,421 (7)	1,147,459 (3)	65 (4)	1,477,911 (3)
			ME	−420,648 (6)	1,249,981 (4)	61 (2)	1,545,819 (5)
			KF	−217,577 (4)	1,304,783 (5)	109 (6)	1,549,250 (6)
			KF + R(yr-2)	−117,453 (3)	1,329,114 (6)	110 (7)	1,542,109 (4)
	Westside District	7	R(yr-2)	−1,270,643 (2)	6,721,232 (8)	21 (2)	8,220,066 (8)
			2-yr avg.	−2,126,588 (8)	6,086,385 (6)	13 (1)	7,539,876 (7)
			Ricker	−1,663,429 (5)	6,050,276 (5)	33 (7)	7,329,580 (5)
			Ricker SST	−1,251,481 (1)	5,722,005 (3)	34 (8)	6,960,882 (2)
			Ricker AR(1)	−1,600,519 (4)	5,257,502 (1)	26 (4)	6,554,482 (1)
			ME	−1,724,581 (6)	5,340,260 (2)	22 (3)	6,984,304 (3)
			KF	−1,850,611 (7)	6,036,440 (4)	31 (6)	7,393,274 (6)
			KF + R(yr-2)	−1,560,627 (3)	6,153,024 (7)	26 (5)	7,298,160 (4)
	Alitak District	7	R(yr-2)	−195,706 (1)	3,058,618 (7)	65 (5)	4,447,579 (8)
			2-yr avg.	−792,919 (6)	2,614,272 (3)	36 (3)	3,732,616 (3)
			Ricker	−1,154,459 (8)	2,560,946 (2)	22 (1)	3,573,285 (1)
			Ricker SST	−1,027,880 (7)	2,505,744 (1)	27 (2)	3,585,208 (2)
			Ricker AR(1)	−525,921 (5)	3,113,463 (8)	74 (7)	4,343,522 (7)
			ME	−434,128 (4)	2,688,314 (4)	57 (4)	3,866,069 (4)
			KF	−417,717 (3)	3,052,200 (5)	78 (8)	3,905,299 (5)
			KF + R(yr-2)	−306,711 (2)	3,054,236 (6)	72 (6)	3,995,514 (6)

TABLE A.1.—Continued.

Region	Stock or District	*n*	Model	MRE	MAE	MPE	RMSE
Kodiak Island	Eastside-Northend District	7	R(yr-2)	673,307 (8)	2,534,831 (2)	91 (2)	3,938,546 (2)
			2-yr avg.	299,372 (4)	2,316,658 (1)	83 (1)	3,194,720 (1)
			Ricker	21,779 (1)	3,402,532 (5)	143 (4)	4,778,908 (7)
			Ricker SST	195,438 (2)	3,482,664 (6)	149 (5)	5,014,262 (8)
			Ricker AR(1)	−319,665 (5)	2,948,261 (4)	132 (3)	4,015,016 (3)
			ME	581,995 (7)	3,501,107 (7)	172 (7)	4,615,877 (5)
			KF	269,521 (3)	3,522,696 (8)	211 (8)	4,741,799 (6)
			KF + R(yr-2)	471,414 (6)	2,923,396 (3)	151 (6)	4,197,823 (4)
	Mainland District	7	R(yr-2)	116,015 (1)	423,851 (2)	22 (1)	556,997 (1)
			2-yr avg.	450,447 (7)	720,321 (8)	59 (6)	884,082 (8)
			Ricker	331,009 (4)	522,161 (4)	57 (4)	605,499 (4)
			Ricker SST	376,980 (6)	467,165 (3)	61 (7)	566,453 (2)
			Ricker AR(1)	336,223 (5)	538,041 (5)	57 (5)	622,894 (5)
			ME	662,091 (8)	693,074 (7)	89 (8)	794,841 (7)
			KF	216,627 (3)	570,573 (6)	56 (3)	728,083 (6)
			KF + R(yr-2)	166,321 (2)	402,593 (1)	39 (2)	566,648 (3)
Chignik	Chignik Bay District	21	R(yr-2)	1,419 (1)	102,495 (2)	44 (2)	127,676 (2)
			2-yr avg.	−10,502 (5)	92,264 (1)	68 (5)	114,842 (1)
			Ricker	−10,417 (4)	117,758 (3)	43 (1)	151,525 (3)
			Ricker SST	16,934 (6)	136,956 (7)	93 (7)	172,371 (7)
			Ricker AR(1)	6,468 (3)	122,957 (5)	59 (4)	164,138 (6)
			ME	−2,159 (2)	122,850 (4)	55 (3)	156,708 (5)
			KF	61,185 (8)	172,992 (8)	120 (8)	215,064 (8)
			KF + R(yr-2)	31,302 (7)	124,776 (6)	82 (6)	151,905 (4)
	Central District	24	R(yr-2)	−58,046 (5)	143,496 (1)	41 (1)	227,525 (1)
			2-yr avg.	−84,598 (8)	174,173 (3)	95 (6)	256,382 (3)
			Ricker	−69,596 (6)	176,084 (4)	62 (2)	288,893 (4)
			Ricker SST	−30,626 (3)	223,973 (7)	96 (8)	322,555 (6)
			Ricker AR(1)	−71,172 (7)	184,322 (5)	69 (4)	311,718 (5)
			ME	−26,718 (1)	225,618 (8)	95 (7)	328,597 (7)
			KF	−29,297 (2)	218,933 (6)	95 (5)	335,828 (8)
			KF + R(yr-2)	−43,671 (4)	165,719 (2)	68 (3)	247,103 (2)
	Eastern District	24	R(yr-2)	−99,279 (2)	391,079 (4)	21 (1)	533,539 (3)
			2-yr avg.	−135,979 (6)	317,688 (1)	27 (2)	458,904 (1)
			Ricker	104,218 (3)	367,786 (3)	76 (4)	542,852 (4)
			Ricker SST	123,310 (5)	400,843 (5)	80 (5)	555,170 (6)
			Ricker AR(1)	179,121 (7)	404,214 (7)	88 (7)	616,685 (7)
			ME	240,128 (8)	457,126 (8)	112 (8)	651,735 (8)
			KF	116,685 (4)	401,746 (6)	82 (6)	555,094 (5)
			KF + R(yr-2)	8,703 (1)	360,871 (2)	51 (3)	516,611 (2)
	Western District	24	R(yr-2)	−27,542 (3)	381,406 (8)	45 (1)	496,152 (8)
			2-yr avg.	−36,577 (5)	350,860 (6)	55 (5)	434,922 (6)
			Ricker	−22,288 (2)	290,214 (1)	60 (6)	389,404 (1)
			Ricker SST	69,987 (8)	377,142 (7)	92 (8)	493,161 (7)
			Ricker AR(1)	−6,009 (1)	294,677 (2)	63 (7)	391,173 (2)
			ME	−32,419 (4)	306,149 (4)	51 (4)	415,899 (5)
			KF	−46,905 (7)	300,353 (3)	49 (3)	398,264 (3)
			KF + R(yr-2)	−37,223 (6)	311,317 (5)	47 (2)	407,503 (4)
	Perryville District	24	R(yr-2)	−26,692 (2)	247,750 (7)	40 (1)	321,689 (3)
			2-yr avg.	−43,275 (3)	243,754 (5)	71 (3)	324,423 (4)
			Ricker	65,211 (5)	235,928 (3)	98 (5)	335,287 (7)
			Ricker SST	96,145 (8)	254,718 (8)	153 (8)	331,950 (6)
			Ricker AR(1)	80,540 (6)	247,027 (6)	107 (6)	353,752 (8)
			ME	88,814 (7)	240,720 (4)	139 (7)	317,189 (2)
			KF	58,249 (4)	233,156 (1)	94 (4)	329,222 (5)
			KF + R(yr-2)	15,829 (1)	235,765 (2)	67 (2)	313,454 (1)

TABLE A.1.—Continued.

Region	Stock or District	n	Model	MRE	MAE	MPE	RMSE
Alaska Peninsula	Northwestern District	25	R(yr-2)	−6,164 (1)	64,260 (1)	40 (1)	138,122 (1)
			2-yr avg.	−10,138 (2)	72,258 (2)	90 (2)	150,479 (2)
			Ricker	90,179 (7)	148,043 (7)	408 (6)	312,963 (7)
			Ricker SST	63,062 (5)	114,645 (4)	579 (8)	224,004 (4)
			Ricker AR(1)	100,858 (8)	159,459 (8)	458 (7)	330,273 (8)
			ME	58,434 (4)	120,778 (5)	397 (5)	245,086 (5)
			KF	71,269 (6)	137,284 (6)	363 (4)	273,392 (6)
			KF + R(yr-2)	32,552 (3)	91,797 (3)	201 (3)	192,945 (3)
	Southeast District and South-central District	25	R(yr-2)	−521,027 (5)	2,799,542 (6)	−1 (1)	3,583,332 (6)
			2-yr avg.	−838,309 (7)	2,525,731 (3)	13 (5)	3,246,123 (3)
			Ricker	−160,678 (2)	2,560,748 (4)	18 (7)	3,319,619 (4)
			Ricker SST	886,453 (8)	3,437,951 (8)	19 (8)	4,695,419 (8)
			Ricker AR(1)	−531,027 (6)	2,038,218 (1)	10 (4)	2,881,765 (1)
			ME	164,473 (3)	2,618,887 (5)	9 (3)	3,337,985 (5)
			KF	−17,046 (1)	2,940,563 (7)	18 (6)	4,265,577 (7)
			KF + R(yr-2)	−269,036 (4)	2,492,519 (2)	8 (2)	3,223,303 (2)
	Southwest District and Unimak District	25	R(yr-2)	−233,611 (5)	1,852,291 (8)	32 (3)	2,378,093 (6)
			2-yr avg.	−375,192 (8)	1,507,906 (5)	38 (4)	1,878,758 (3)
			Ricker	26,016 (1)	1,434,321 (3)	60 (6)	1,865,664 (2)
			Ricker SST	353,686 (7)	1,440,766 (4)	30 (2)	2,451,299 (7)
			Ricker AR(1)	232,270 (4)	1,403,672 (2)	81 (8)	1,897,445 (4)
			ME	−190,649 (3)	1,174,040 (1)	18 (1)	1,544,083 (1)
			KF	300,403 (6)	1,852,265 (7)	62 (7)	2,579,758 (8)
			KF + R(yr-2)	33,396 (2)	1,704,017 (6)	47 (5)	2,296,367 (5)
Bristol Bay	Nushagak District	7	R(yr-2)	675,925 (1)	1,721,474 (1)	302 (1)	2,580,676 (1)
			2-yr avg.	1,612,594 (2)	2,299,848 (2)	314 (2)	3,137,290 (2)
			Ricker	4,845,752 (5)	4,860,097 (5)	1,134 (5)	6,233,356 (5)
			Ricker SST	9,259,864 (8)	9,259,864 (8)	2,055 (8)	14,770,012 (8)
			Ricker AR(1)	5,454,322 (6)	5,454,322 (6)	1,225 (6)	6,966,934 (6)
			ME	6,907,571 (7)	6,933,512 (7)	1,317 (7)	10,904,159 (7)
			KF	4,112,796 (4)	4,153,350 (4)	1,017 (4)	5,410,174 (4)
			KF + R(yr-2)	2,394,360 (3)	2,595,489 (3)	660 (3)	3,729,497 (3)
Norton Sound	Nome	7	R(yr-2)	−11,268 (1)	209,157 (1)	155 (1)	332,051 (1)
			2-yr avg.	−68,886 (2)	232,806 (2)	230 (2)	345,605 (2)
			Ricker	398,455 (7)	473,272 (7)	1,263 (7)	709,594 (7)
			Ricker SST	173,728 (4)	275,957 (3)	547 (3)	401,859 (3)
			Ricker AR(1)	439,004 (8)	500,157 (8)	1,454 (8)	731,045 (8)
			ME	365,038 (6)	430,094 (6)	913 (5)	651,571 (6)
			KF	346,302 (5)	428,255 (5)	1,157 (6)	641,395 (5)
			KF + R(yr-2)	167,517 (3)	282,185 (4)	656 (4)	442,489 (4)
	Golovin	7	R(yr-2)	362,253 (4)	463,654 (4)	478 (6)	693,690 (4)
			2-yr avg.	283,864 (3)	365,764 (3)	334 (3)	660,167 (3)
			Ricker	532,690 (7)	707,191 (7)	396 (4)	1,400,497 (7)
			Ricker SST	141,236 (1)	244,107 (1)	65 (1)	433,726 (1)
			Ricker AR(1)	721,254 (8)	882,655 (8)	464 (5)	1,843,830 (8)
			ME	162,384 (2)	273,488 (2)	112 (2)	519,040 (2)
			KF	497,806 (6)	642,984 (6)	515 (8)	1,191,164 (6)
			KF + R(yr-2)	430,030 (5)	525,836 (5)	496 (7)	930,038 (5)
	Moses Point and Norton Bay	14	R(yr-2)	−117,872 (6)	276,519 (5)	33 (1)	423,883 (7)
			2-yr avg.	−128,496 (7)	253,026 (3)	51 (2)	422,792 (6)
			Ricker	−57,582 (4)	302,728 (6)	281 (6)	416,344 (5)
			Ricker SST	−145,581 (8)	227,652 (2)	124 (3)	363,626 (2)
			Ricker AR(1)	−26,206 (2)	308,772 (7)	312 (7)	401,829 (3)
			ME	−85,429 (5)	217,338 (1)	190 (4)	330,346 (1)
			KF	−4,592 (1)	366,213 (8)	424 (8)	527,871 (8)
			KF + R(yr-2)	−61,232 (3)	264,226 (4)	229 (5)	411,376 (4)

TABLE A.1.—Continued.

Region	Stock or District	*n*	Model	MRE	MAE	MPE	RMSE
Norton Sound	Unakleet	13	R(yr-2)	−29,857 (1)	127,242 (1)	123 (1)	200,110 (2)
			2-yr avg.	−31,457 (2)	142,398 (2)	202 (2)	198,248 (1)
			Ricker	138,454 (5)	324,581 (7)	688 (7)	430,318 (7)
			Ricker SST	117,252 (4)	266,693 (4)	635 (5)	359,599 (4)
			Ricker AR(1)	167,635 (8)	325,535 (8)	686 (6)	461,813 (8)
			ME	152,796 (6)	277,090 (5)	556 (3)	365,068 (5)
			KF	165,919 (7)	319,196 (6)	1,117 (8)	418,430 (6)
			KF + R(yr-2)	68,031 (3)	194,485 (3)	620 (4)	260,118 (3)