EVALUATION OF SALMONID SURVIVAL RESULTING FROM FLOW ALTERATIONS TO THE LOWER YAKIMA RIVER

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1.0 Executive Summary

The Kennewick Irrigation District (KID) and United States Bureau of Reclamation (USBR) are considering a range of alternatives that would result in less water being diverted at Prosser Dam resulting in greater flows in the lower Yakima River. The primary motivation for this work is the assumption that increased instream flows will increase survival of emigrating salmonids and ultimately result in improved adult salmonid returns to the Yakima River. Previous studies have not always found that increased flows improve survival of emigrants or smolt to adult (SAR) return rates. The purpose of this study was therefore to estimate the impacts of increased flow on emigrating salmonids, and to estimate the potential benefit of implementation of each of the seven alternatives being considered. We analyzed passive integrated transponder (PIT) tag data from year 1998-2004 for spring Chinook, fall Chinook and coho salmon emigrating between Prosser Dam and McNary Dam. There were not enough PIT tag data to estimate survival for steelhead, so we assumed that steelhead and spring Chinook would respond in a similar fashion to changes in flow. This assumption is questionable given the differences in life histories between steelhead and Chinook. Thus, the results of this study may not reflect actual influences of the pump exchange project on steelhead populations. However, given the lack of PIT tag data for steelhead and of the salmonids present in the Yakima River, Chinook salmon were thought to be the best surrogate for steelhead. We emphasize that in order to quantify the impact of flow and other environmental variables on steelhead, an expanded tagging effort is required. To estimate changes in adult abundance, we used the recent 15-year geometric mean of adults to Prosser Dam, as well as projected abundance resulting from basin wide habitat improvements.

Our results show that flow had a strong effect on Prosser to McNary survival rates for fall Chinook, an intermediate effect for coho, and a minimal effect for spring Chinook and steelhead (since we assumed spring Chinook and steelhead were comparable). Commensurate with flow-survival relationships, estimated increases in smolts surviving to McNary, and adults returning to Prosser were relatively high for fall Chinook, intermediate for coho, and minimal for spring Chinook and steelhead. In general, the data suggest that increasing flow will result in higher survival of emigrating smolts between Prosser and McNary Dams. The relationships, however, are subject to many qualifiers as the data are highly variable.

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2.0 Introduction

The Kennewick Irrigation District in partnership with the Columbia Irrigation District, Yakama Indian Nation and the United States Bureau of Reclamation has proposed a project to reduce the amount of water diverted for irrigation from the lower Yakima River. The goal of this "Pump Exchange" project is to increase the survival of emigrating juvenile salmon and ultimately increase the number of returning adults by reducing the amount of water diverted from the Yakima River for irrigation.

Currently, water is diverted at two locations for the Kennewick and Columbia Irrigation Districts (Figure 1). Prosser Dam is located at river mile 47.1, and is used to divert water into the Chandler Canal. Chandler canal has a capacity of approximately 1500 cfs. Of this, approximately 740 cfs is diverted for irrigation. Of the water diverted for irrigation, 330 cfs is actually delivered to the Kennewick Irrigation District. The remaining portion (410 cfs) is returned to the Yakima River eleven miles downstream at the Chandler Powerhouse. The reason the Kennewick Irrigation District diverts more water than is delivered to the canal is that the pumps used to fill the canal are driven by hydraulic head as opposed to electricity. The additional water is used to operate the pumps. The Columbia Irrigation District diverts 200 cfs from the Yakima at river mile 18 at Wanawish Dam (formerly Horn Rapids Dam). Electrification of exchange would mean that less water would need to be diverted at Prosser Dam in order to meet the needs of the Kennewick Irrigation District. This would leave more water in the Yakima River during the irrigation season. Thus, less water could be diverted at Prosser and Wanawish dams leaving more water in the Yakima River during the irrigation season.

There are eight alternative management actions under consideration to achieve to the goal of leaving more water in the Yakima River. Each alternative returns a different amount of water to the Yakima River at different locations. These alternatives are defined here as:

- (1) No action;
- (2) Electrification of Chandler pump plant;
- (3a) Partial KID exchange;
- (3b) Chandler Electrification & Partial KID Exchange;
- (3c) Partial KID & Partial CID Exchange;
- (3d) Chandler Electrification & Partial KID & Partial CID Exchange;
- (4a) Full KID Exchange; and
- (4b) Full KID & Partial CID Exchange.

Considerable effort has been expended in developing estimates of the potential benefits of each alternative in terms of increases in emigration survival for juveniles and subsequent adult returns. Much of this work was done by Mr. Steve Croci of the United States Fish and Wildlife Service. An essential element of Mr. Croci's analysis was the assumed functional relationship between flows in the lower Yakima River and emigration survival of juvenile salmon. Relationships were derived for spring Chinook, fall Chinook, and coho salmon based on analyses of three years (1999-2001) of PIT tag data provided by Neeley (2002). PIT tag data are by far the best source of information available to assess potential benefits of each alternative. Since that time, however, PIT tag data have been collected for three additional years (2002-2004).

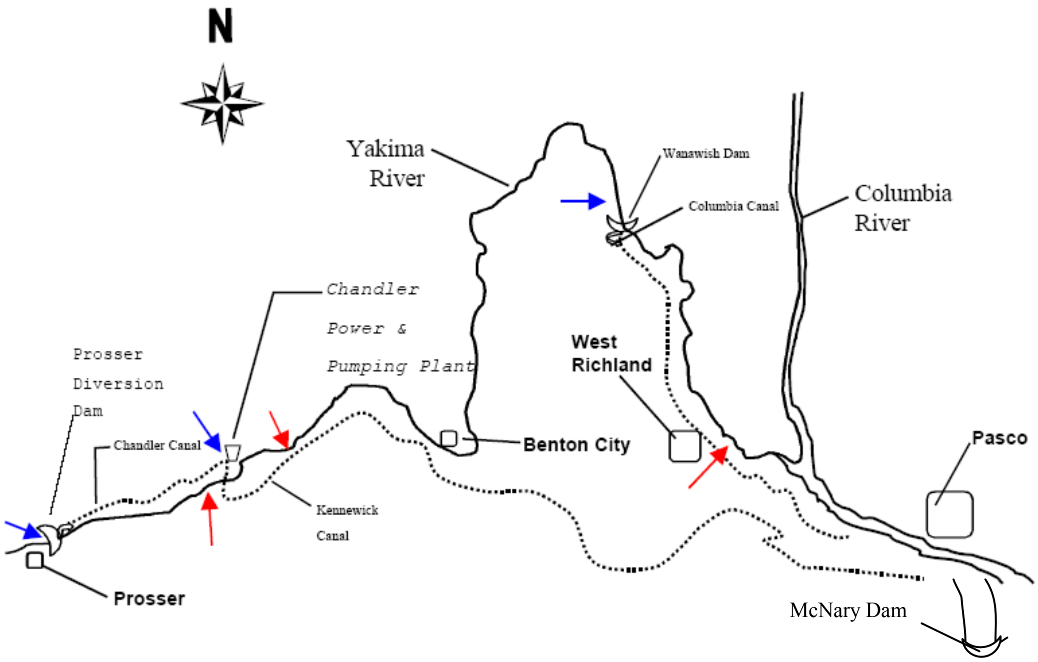


Figure 1. Schematic of the lower Yakima River showing Prosser, Wannawish, and McNary Dams and Chandler.

The goal of this report was to further refine the assessment of benefits for each alternative. In particular, we rigorously evaluated relationships between river flow and survival rates of juvenile salmon in the lower Yakima River using additional years of PIT tag data for spring Chinook, fall Chinook, and coho salmon. Building on Mr. Croci's analysis, we then used the flow-survival relationships derived from PIT tag data to estimate increases that would result under each alternative in emigration survival and subsequent adult returns to the Yakima River of spring Chinook, fall Chinook, and coho salmon. Consistent with Mr. Croci's analysis, estimates of benefits were based on three representative "year types" for flow conditions (dry, average, and wet). This was done so that results of a hydrologic model that was used to estimate flow increases under each alternative could be appropriately applied to juvenile emigration data. However, as we discuss, our approach to estimating adult returns differed from that used by Mr. Croci.

We caution the reader that each step of this analysis involved a set of assumptions, and with each step, uncertainty increased. As a result, estimates of "benefits" were highly uncertain, particularly when extrapolated to adult returns. In fact, estimates of potential increases in adult returns were speculative at best. We attempted where possible to quantify uncertainties and examine the implications of alternative assumptions using sensitivity analyses. Further, we discuss the limitations of our study and possible approaches to better quantify uncertainties to facilitate decision making.

2.1. Study area and Yakima River characteristics

The lower Yakima River extends 43 miles from Prosser Dam to the Columbia River in south central Washington State draining an estimated 618 km^2. The reach between Prosser Dam and Chandler has been characterized as confined with little ability to support over bank flow, or channel migration (Ring and Watson 1999). The Yakima River basin supports large amounts of agriculture with the attendant need for irrigation water. The result is the Yakima River flows and diversions are intensely monitored, and runoff amounts and timing are well documented.

The Yakima River at Prosser is characterized by a high spring runoff peaking in March, and low summer flows reaching a minimum in August (Figure 2, Table 1). There is a tremendous amount of variation in this pattern and the timing of high or low flows can overlap by several months. The Chandler Canal is filled at Prosser, and typically conveys 1000 cfs with a maximum of 1500 cfs over the course of a year (Figure 2). Chandler Canal is used to supply the Kennewick Irrigation District and to generate power and is only operated from March to October with April through September representing months of continuous operation (Figure 2). Peak discharge in the Kennewick canal is reached in July.

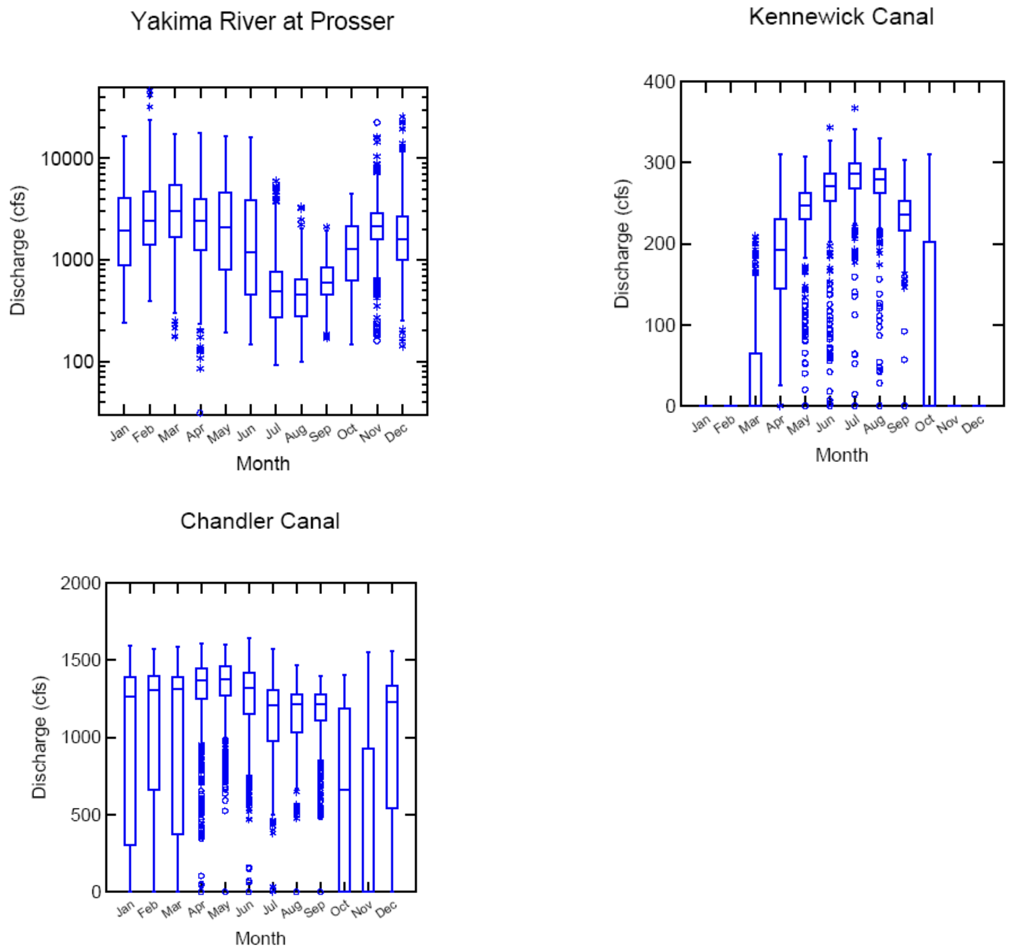


Figure 2. Average flows for the Yakima near Prosser, Kennewick Canal and Chandler Canal. Boxes represent 25 to 75 percentile, lines representing the median, and whiskers represent the 10 and 90th percentile. Graphs from WDOE (2001).

Table 1. Mean monthly river flow for the Yakima River below Prosser Dam.

Year	March	April	May	June	July	August
1981	2800	465	1015	569	369	296
1982	4807	1632	4377	5021	1454	553
1983	8428	4709	5545	4187	1009	634
1984	3852	2256	2855	6022	973	360
1985	1842	3066	1367	1176	225	345
1986	7734	2436	954	720	383	195
1987	3443	1497	2167	267	233	184
1988	642	1628	823	502	246	300
1989	1853	4004	2247	643	285	301
1990	1904	3425	1984	3349	406	910
1991	2621	2743	1822	2420	1015	603
1992	2411	886	729	429	474	360
1993	2220	2211	1490	619	378	430
1994	947	1330	809	376	268	378
1995	6092	2839	5377	2437	794	593
1996	7940	6532	3756	2594	743	672
1997	8712	12560	13257	6395	1763	963
1998	3622	2595	7077	3438	712	608
1999	4062	3603	5014	8071	3231	994
2000	2989	5006	2936	3136	596	527
2001	1123	747	696	515	459	392
2002	1807	3334	5429	901	551	565
2003	3438	2817	2230	2229	482	543
2004	2877	2209	1298	921	-	-

3.0 Methods

We estimated the potential benefits of increased flows in terms of expected increases in the number of smolts (emigrating juvenile salmon) at McNary dam and subsequent adult returns for spring Chinook, fall Chinook, and coho salmon of the Yakima Basin. Our analyses relied heavily on seven years of PIT tag data (1998-2004). There were four general steps to our analyses:

(1) Estimate survival rates from Prosser to McNary;
(2) Estimate relationships between flow and survival;
(3) Estimate increases in smolt abundance for each alternative flow scenario; and
(4) Estimate increases in adult returns.

We first provide a brief description of expected flow increases for each alternative, followed by detailed methods for each of the above steps.

3.1. Alternative flow scenarios

Estimates of the amount of water retuned to the Yakima River for each alternative were developed by the United States Bureau of Reclamation (Steve Croci, personal communication) using a hydrology model. Estimates of average additional discharge from April through September were provided for three historic years (Table 2). Because estimates of additional discharge were conditional on the general flow conditions experienced in a given year, the three years in Table 2 were selected as representative of three general "year types:" a dry year (1994), an average year (1990), and a wet year (1996). As discussed below, these general year types were matched with three recent years for which estimates of emigration survival and fish passage at Prosser were available. By adding the incremental discharge estimates in Table 2 to the historic daily flows in a given year, each alternative management action provided a different "flow scenario" used to estimate increases in emigration survival and adult returns.

Note that estimates developed from the hydrology model were adjusted to account for the location at which additional water was added to the Yakima River under each alternative (Table 2). The adjustment took the form of weighting the amount of additional water based on the river mile at which the water was added. The premise of the weighting was that water added downstream of Prosser has less value than water added at Prosser, since fish will be exposed to increased discharge for a shorter reach of river. Since fish survival was estimated as a function of river discharge at Prosser Dam, it was deemed necessary to discount water that was added further downstream. For example, Prosser is at river mile 47.1, and Chandler is at river mile 35.8. If an additional 100 cfs is added to the Yakima River at Chandler, then the benefit of this water was weighted according to this calculation: $Q_{weighted} = (D_{rm}/U_{rm})*Q_a$ where $Q_{weighted}$ is the weighted value of added water, D_{rm} is the downstream river mile location at which water was added, U_{rm} is the upstream river mile location from which survival estimates were estimated (in this case Prosser Dam), and Q_a is the amount of additional water added. Thus, an additional 100 cfs added at Chandler is equal to (35.8 river mile/47.1 river mile)*100 cfs = 76 cfs added at Prosser.

Table 2. Estimated additional discharge (cfs) remaining in the Yakima River for each alternative. Adjusted flows are normalized to Prosser and reflect that water added downstream of Prosser has less potential to impact survival than water added at Prosser.

Yakima River Location	River Mile	Alternative Management Action						
		2[2]	3a[3]	3b[4]	3c[5]	3d[6]	4a[7]	4b[8]
		Dry Year (1994) Apr-Sep Average						
Near Prosser	47.1	286	308	421	308	421	511	511
Near Kiona	35.8	0	129	134	129	134	219	219
Below Wanawish Dam	18	0	0	0	87	87	0	87
Adjusted Kiona		0	98	102	98	102	166	166
Adjusted Wanawish		0	0	0	33	33	0	33
Adjusted flow at Prosser		**287**	**406**	**523**	**439**	**556**	**677**	**710**
		Average Year (1990) Apr-Sep Average						
Near Prosser	47.1	364	389	526	389	526	634	634
Near Kiona	35.8	0	156	158	156	158	266	266
Below Wanawish Dam	18	0	0	0	108	108	0	108
Adjusted Kiona		0	119	120	119	120	202	202
Adjusted Wanawish		0	0	0	41	41	0	41
Adjusted flow at Prosser		**364**	**508**	**646**	**549**	**687**	**836**	**877**
		Wet Year (1996) Apr-Sep Average						
Near Prosser	47.1	337	360	485	360	485	583	583
Near Kiona	35.8	0	143	143	143	143	238	238
Below Wanawish Dam	18	0	0	0	99	99	0	99
Adjusted Kiona		0	109	109	109	109	181	181
Adjusted Wanawish		0	0	0	38	38	0	38
Adjusted flow at Prosser		**337**	**469**	**594**	**507**	**631**	**764**	**802**

[2]Chandler Electrification, [3]Partial KID Exchange, [4]Chandler Electrification & Partial KID Exchange, [5]Partial KID & Partial CID Exchange, [6]Chandler Electrification & Partial KID & Partial CID Exchange, [7] Full KID Exchange, [8] Full KID & Partial CID Exchange

3.2. Estimates of survival rates

We used seven years of PIT tag data (1998-2004) to estimate survival rates of juvenile salmon migrating from Prosser Dam to McNary Dam. Survival rates were estimated for numerous “release groups” within a given year, where each release group was defined as those fish detected as passing Prosser on a given day. We therefore refer to these as “daily” release groups and “daily” survival-rate estimates.

Specifically, the survival rate (s) of a given release group was estimated as:

(1) $$s = \frac{r}{R} ,$$

where R was the number of fish in the release group (i.e., the number detected at Prosser on a given day) and r was the estimated number of fish that survived to McNary. The latter was computed by summing across daily passage estimates (r_i) at McNary:

(2) $$r = \sum_i r_i = \sum_i \frac{d_i}{p_i} ,$$

where d_i was the number detected at McNary on day i, and p_i was the detection probability for that day.

Daily detection probabilities (p_i) at McNary were estimated using methods similar to those used by Neeley (2002) and Sanford and Smith (2002). Specifically, detection probabilities were computed using data for all Yakima-released smolts of a given species that were detected at McNary and downstream dams (John Day and Bonneville). This approach differed markedly from the standard Jolly-Seber-Cormach (JSC) method (or variants thereof), in which detection probabilities are computed using only data specific to the release group of interest. In contrast, our approach capitalized on the fact that far more detections were available than just those defined by a single release group. As a result, we were able to estimate detection probabilities and survival rates for many more release groups than was possible using the JSC method.

Initially, survival rates were estimated for four different categories or "release types" of juveniles passing Prosser:

(1) Wild fish tagged and released at or near Prosser;
(2) Wild fish tagged and released well above Prosser;
(3) Hatchery fish tagged and released at or near Prosser; and
(4) Hatchery fish tagged and released well above Prosser.

We used these different "release types" to account for potential differences in survival rates among wild versus hatchery fish, as well as among fish tagged at or near Prosser versus those tagged well above Prosser. Such differences in survival were tested for in the regression analyses discussed below. If large differences existed but were not accounted for, they could bias or confound the assessment of flow-survival relationships. However, separating fish into groups reduces release sizes (R) and thereby increases uncertainty in survival-rate estimates. Therefore, if little difference in mean survival was found among release types, the groups were pooled and survival rates were re-estimated for the pooled groups.

3.3. Relationships between flow and survival

3.3.1. Logistic regression

We used logistic regression to examine the potential effects of flow, as well as other variables, on survival rates of each species. Logistic regression is a form of "generalized linear model" (GLM) that is applicable to binomial data (McCullach and Nelder 1989; Dobson 2002). The general model with *n* explanatory variables (*x*) can be expressed in linear form as:

(3) $$y = \beta_1 + \beta_2 x_2 + \ldots + \beta_n x_n$$

where *y* is the "logit" transform of the survival-rate estimates (*s*):

(4) $$y = \text{logit}(s) = \log\left(\frac{s}{1-s}\right).$$

The coefficients (β) are estimated via maximum likelihood, and provide predicted values of survival rate via the following back-transformation of logistic model:

(5) $$\hat{s} = \frac{\exp(\hat{\beta}_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_n x_n)}{1 + \exp(\hat{\beta}_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_n x_n)}.$$

An underlying assumption of this logistic regression model is that the number surviving (*r*) for any given release group is a *binomial variable*, conditional on the survival rate (*s*) and the number released (*R*) (equation 1). Formally, we denote this $r \sim$ binomial(R, s). Under the binomial model, an estimate of survival rate (*s*, the *binomial probability*) has theoretical variance:

(6) $$\text{var}(s) = \frac{s(1-s)}{R}.$$

Thus, the variance of *s* is inversely proportional to the release-group size *R*. This is accounted for in the fitting procedure for logistic regression, where values of *R* are used as *weights* in a manner analogous to weighted-least-squares methods. The implications are intuitive: the survival estimate for a release group of 500 fish will be more precise and have greater "weight" than that for only 50 fish.

However, mark-recapture data often do not conform to the binomial assumption. This was true for the data used here because the number surviving (*r*) was not observed precisely; rather, it was an expanded estimate based on estimated detection probabilities (equation 2). Consequently, variances will tend to be greater than expected under the binomial assumption. This phenomenon is known as *over-dispersion*, which generally refers to the case where observations of the dependent variable have greater sampling variance than assumed under the GLM.

We applied two approaches to account for potential over-dispersion. First, we modified the weights used in the logistic regression to (approximately) account for the estimation of r via detection probabilities. Under the approximate assumption of sampling with replacement, total detections (across all days) at McNary were assumed to be binomially distributed: $d \sim$ binomial(r, p), where d is the number detected, r is the (unknown) number surviving, and p is the detection probability. Combining both survival and detection processes results in a single binomial model: $d \sim$ binomial(R, $s*p$). It can be shown from this compound distribution that the theoretical variance for the survival rate (s) is approximately:

(7) $$\mathrm{var}(s) \cong \frac{s(1-sp)}{Rp}.$$

The variance of s is now inversely proportional to $R*p$, the release-group size multiplied by the detection probability. We therefore used *weights* in logistic regressions equal to $R*p$, where p was the weighted average of the daily detection probabilities at McNary for a given release group. The implications are again intuitive: the survival estimate for a release group of 500 fish that had an average detection probability at McNary of 70% will be more precise and have greater "weight" than that for 500 fish with a detection probability of only 30%.

Note, however, that this is only an approximate adjustment to the variance and weights. For example, it does not account for uncertainty in estimates of detection probabilities (implying greater sampling variance than assumed), and the variance implied in the logistic model still assumes the term (1 - s) in the numerator of equation 6 rather than (1 - sp) as in equation 7 (again implying greater sampling variance than assumed).

Even with the above adjustment to the model weights, we found that the estimated *deviance* (analogous to the residual sum of squares in normal linear regression) of a given logistic model often greatly exceeded the theoretical deviance of the so-called *saturated* model. The latter is the deviance when all y [= logit(s)] are treated as "free" parameters, that is, the expected deviance due to sampling error only. Such a discrepancy between observed and theoretical deviances may arise from either over-dispersion or inadequate model structure (i.e., when key processes affecting survival rates are missing from the model). This is an important distinction because variances of regression coefficients will be underestimated in the case of over-dispersion, but not in the case of inadequate model structure. Because we estimated each y using a limited set of explanatory variables, we expect that some *real* variation in survival rates (due to factors other than sampling error) will not be explained, and hence, model deviance should be greater than expected due to inadequate model structure. On the other hand, we also expect that our logistic formulation underestimates the true sampling error, as noted above.

Given that some level of additional over-dispersion was anticipated but not readily quantifiable, we used a conservative approach to estimating variances and testing regression coefficients.

Specifically, we assumed that *all* unexplained deviance above the theoretical deviance was due to over-dispersion. This can be represented by a dispersion parameter, ϕ, which is a scalar of the assumed logistic variance (i.e., *assumed variance* * ϕ). A value of ϕ close to one implies little over-dispersion, whereas a value of 4, for example, indicates considerable over-dispersion. The dispersion parameter is easily estimated from the fit of a logistic regression and does not affect point estimates of coefficients (Venables and Ripley 1999). However, the variance-covariance matrix for coefficients must be multiplied by the estimate of ϕ to account for potential over-dispersion. For this reason, the dispersion parameter is sometimes referred to as the *variance inflation factor*.

3.3.2. Explanatory variables

In addition to flow, we considered several other explanatory variables (x) that might influence survival rates. The complete set of variables was:

(1) Daily flow at Prosser;
(2) Water temperature at Prosser;
(3) Median travel time between Prosser and McNary;
(4) Julian day of migration;
(5) Release type (wild, hatchery, at or near Prosser, or well above Prosser); and
(6) Year

Daily flows, temperatures, and day of migration corresponded to the day of detection at Prosser (i.e., the day of passage used to define each release group). While variables (1)-(4) were treated as continuous variables, *release type* and *year* were included as factors to account for potential differences in mean survival rate across release types or years that may unrelated to the other variables. In equation (3), a factor can expressed by denoting a dummy variable (x = 0 or 1) for each level of the factor (in our case, for each release type or each year). For example, $x_{1999} = 1$ for all 1999 data and $x_{1999} = 0$ for all other years.

Thus, our approach was to fit a logistic model to <u>all</u> years of available data. This approach assumes that relationships between survival and an explanatory variable (e.g., flow) will have a similar form across years. An alternative would be to fit each year separately, but this has several disadvantages. First, we are interested in establishing a predictive relationship between flow and survival that can be generalized across years. Modeling each year separately, however, implies that flow-survival relationships may differ appreciably between years, and may therefore have little applicability from year to the next (i.e., little predictive power). Second, modeling separate years would also allow relationships between survival and other variables (e.g., temperature) to differ appreciably among years (e.g., a negative effect of high temperatures in one year, but a positive effect in a different year). Such differences would likely have little biological support and would be considered spurious. In contrast, modeling all years simultaneously provides fewer models and more data, which reduces the chance of finding spurious relationships and increases the statistical power to detect relationships that have a <u>consistent</u> basis across years.

Because our primary focus was to depict potential relationships between flow and survival, we considered three approaches to modeling flow. Examples of each approach are shown in Figure 3. First, we used raw flows as an explanatory variable (*x*), which assumes a linear relationship between flow and logit(survival) (equation 3). This formulation often produced somewhat linear relationships between flow and survival, such as that depicted in Figure 3. Second, we used log(flow) as an explanatory variable, which implied greater curvature in the flow-survival relationship (Figure 3). A priori, we expect that survival rates will tend to be low at very low flows, but may increase rapidly as flows increase. Above some intermediate flow, however, we expect little influence of flow on survival. This conceptual model is better depicted by using log(flow) as the explanatory variable. Even for log(flow), the relationship assumes some tendency for survival to increase at high flows. We therefore considered a third model, in which survival was unaffected by flow above some intermediate flow. We refer to this as the "broken-stick" model (Figure 3). The ascending limb of the model assumes a linear relationship between flow and logit(survival) up to a "critical" or breakpoint flow, after which there is no affect of flow on survival.

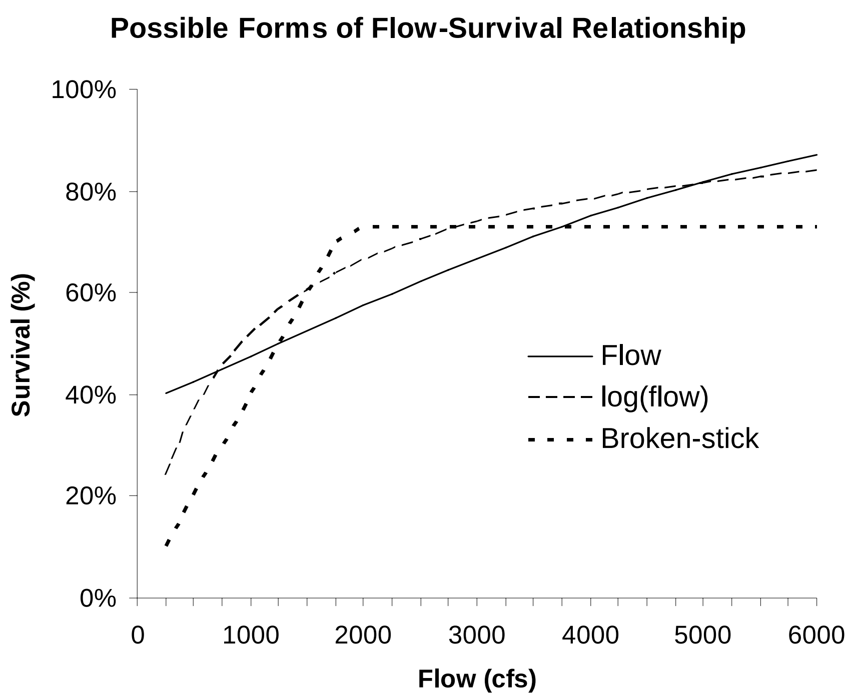


Figure 3. Example relationships between flow and survival rate for three model forms: (1) a linear relationship between flow and logit(survival) (the "Flow" model); (2) a linear relationship between log(flow) and logit(survival) (the "log(flow)" model); and (3) the "broken-stick" model in which logit(survival) is linearly related to flow up to a "critical" or breakpoint flow, above which flow has no effect.

3.3.3. Model selection and testing

We used a stepwise regression procedure to determine which variables to include in a given logistic model. In the first step, a model was fit with an intercept ($y = \beta_1$), and then each explanatory variable (*x*) was entered one at a time. The variable with the greatest explanatory power was then included in the model ($y = \beta_1 + \beta_2 x_2$), and the remaining variables were again entered one at a time. The procedure was terminated when none of the remaining variables had a statically significant effect on survival at the $\alpha = 0.05$ significance level.

An alternative approach to model selection was also examined. In this approach, the "best" model was determined using the Akaike Information Criterion (AIC), adjusted for over-dispersion (Burnham and Anderson 2002). This criterion provides a measure of the statistical support of a given model by adjusting the model deviance by a penalty term to account for the number of model parameters. The model with the lowest AIC value is the highest ranking or "best" model. The procedure began by fitting a "global" model to the data; for example, a model that included flow (in its linear form) and all of the other variables (temperature, travel time, year, etc.). The AIC value for this model was then computed as:

(7) $$AIC = \frac{deviance}{\hat{\phi}} + 2K,$$

where $\hat{\phi}$ was the estimated dispersion parameter and *K* was the number of parameters. Variables were then dropped one at a time (or possibly added in later stages) in an automated routine until the model with the lowest AIC value was identified (Venables and Ripley 1999). In this procedure, the estimated dispersion parameter ($\hat{\phi}$) for the global model was used when computing AIC for each alternative model (Burnham and Anderson 2002).

The stepwise regression and AIC procedures provided the same "best" model in all analyses. However, as discussed below, we tested the sensitivity of our results to several alternative models. In these cases, we used AIC values to provide a statistical comparison among the models. The AIC of the best model was subtracted from the AIC values of all other models to facilitate comparisons. This difference in AIC values is denoted Δ_i for the *i*th model, where Δ_i = 0 for the best model and $\Delta_i > 0$ for all others. As a general rule of thumb, Burnham and Anderson (2002) suggest that models with $\Delta_i < 4$ are reasonably strong alternatives to the best model, whereas models with $4 < \Delta_i < 7$ have relatively weak support and models with $\Delta_i > 7$ have very little support given the data.

The resulting "best" model was then examined using standard diagnostics. In addition, we used "generalized additive models" (GAMs) to examine the assumption of linearity between each model variable and logit(survival) (equation 3). These models used a non-parametric smoothing spline to characterize the relationship between each variable and survival, which was then compared to its linear form. At this stage of the modeling exercise, it became evident that relationships between flow and logit(survival) may be better depicted by the "broken-stick" model. GAM plots were used to visually determine the potential "critical" flow (breakpoint) for the broken-stick model, which was then fit to the data. Thus, there was an arbitrary aspect to the construction of the broken-stick models. For this reason, broken-stick models were assigned an additional parameter when computing AIC values.

Analysis of deviance was used to test the significance of explanatory variables in a given logistic regression. Tests were based on F-tests that accounted for over-dispersion (Venables and Ripley 1999). Although such tests are only approximate, we ensured that they were conservative by assuming that all unexplained deviance above the theoretical deviance was due to over-dispersion (discussed above).

3.3.4. Sensitivity analysis

For all three species, the stepwise procedure above provided a base model that included flow or log(flow) as one of the explanatory variables. We then examined the sensitivity of estimated flow-survival relationships by (1) comparing flow-survival relationships among models that differed in the form of that relationship (i.e., flow, log(flow) and broken-stick forms), and (2) sequentially removing each of the other explanatory variables from the model and re-estimating the flow coefficient.

3.4. Effects of flow on smolt abundance

Flow-survival relationships were then used to estimate changes in smolt abundance that may occur if flows below Prosser were increased. To do this, we used emigration and flow data for years 1999, 2001, and 2003. These three years were selected as representative of the general "year types" used to estimate flow increases under each alternative management action (Table 2): a dry flow year (2001), an average flow year (2003), and a wet flow year (1999).

For each year and species, we predicted the total number of smolts (N) passing McNary as follows:

(8) $$N = \sum_i s_i n_i ,$$

where s_i was the predicted Prosser-to-McNary survival rate for fish passing Prosser on day i, and n_i was the abundance of wild juveniles estimated to have passed Prosser on day i. Thus, the overall Prosser-to-McNary survival-rate estimate for a given year and species was simply:

(9) $$s_{\text{P-M}} = N \Big/ \sum_i n_i .$$

Daily survival rates for each year and species were predicted using a given logistic model and flow regime. Next, smolt abundances were estimated using the historic flows for each year, which represent the baseline ("no action") case. These baseline estimates were then compared to smolt estimates derived for each alternative "flow scenario," in which an additional flow increment (Table 2) was added to the historic flow for the specific year type (dry, average, or wet). For a given scenario, the percent increase in smolts surviving to McNary was estimated as:

(10) $$\text{Percent (\%) increase in smolts at McNary} = \left[\frac{N_{Scenario}}{N_{Baseline}} - 1\right] \times 100 \ .$$

3.5. Effects of flow on adult returns

We used a simple approach to estimate potential increases in adult returns to Prosser for each flow scenario. The key assumption was that an increase in smolt abundance at McNary would translate into an exact *proportional* increase in adult returns. That is, if we estimated that a given flow scenario increased the number of smolts surviving to McNary by 10%, then adult returns to Prosser were also assumed to increase by 10%. In other words, annual smolt-to-adult return rates (SARs) from McNary to Prosser were assumed to remain fixed regardless of the abundance of smolts that reached McNary, the day of smolt arrival, or potential changes caused by a given flow scenario to smolt behavior or the habitat conditions they experienced. For reasons outlined in the Discussion, this assumption is optimistic, and hence, we consider our estimates of *proportional* increases in adult abundance to be maximum estimates.

As outlined below, we generated 12 estimates of potential increases in adult returns for each species and flow scenario. These differed in terms of the assumed abundance of returns under current flow conditions (two alternatives), the assumed proportion of year types encountered in the future (two alternatives), and the assumed form of the flow-survival relationship (three alternatives). In addition, we also computed estimates that integrated across the three alternative flow-survival relationships.

3.5.1. Adult returns under baseline flow conditions

Consider the following equation for the number of adult returns at Prosser (R_P):

(11) $$R_P = \text{Smolts}_P * s_{P\text{-}M} * \text{SAR}_{M\text{-}P}$$

where Smolts_P is the number of smolts passing Prosser in a given year, $s_{P\text{-}M}$ is the Prosser-to-McNary survival rate (equation 9), and $\text{SAR}_{M\text{-}P}$ is the smolt-to-adult return rate from McNary to Prosser.

Numerous factors likely influence each component of the right side of equation (11). Our focus was to estimate flow-related differences in $s_{P\text{-}M}$ among year types (wet, average, and dry), but it is also possible that smolt production and/or SAR values differ systematically across year types. For example, general conditions associated with a wet year versus those of a dry year may result in different patterns of fry survival, fry growth, marine survival, and so on. However, after reviewing recent years of data, we concluded that it was not feasible to relate expected passage numbers at Prosser to the general year type, nor was it possible to determine specific McNary-to-Prosser SAR values that may correspond to a typical wet, average, or dry year. While there was evidence of associations between adult returns of each species and the general flow conditions experienced during their year of out-migration, the data provided little guidance as to how passage numbers or SAR values may differ on a consistent basis among year types.

We therefore assumed that future smolt passage and SAR values would be the same for each year type and constant over time. Instead of specifying values for Smolts_P and $\mathrm{SAR}_{M\text{-}P}$, we specified of value for the expected *average* adult return at Prosser ($\overline{R}_P$) under baseline ("no action") flow conditions.

Specifically, we examined two alternative values for expected adult returns by species. The first was the recent 15-year geometric mean of returns observed at Prosser (1990-2004) (Table 3). The second value was the abundance estimated from EDT analyses for "Restoration" reference conditions; details of the EDT analyses are provided in Yakima Subbasin Plan Final Draft, May 28th, 2004. (Available at http://www.nwppc.org/fw/subbasinplanning/yakima/plan/Default.asp). In brief, the analyses provided projections of geometric-mean adult returns by population unit under "Current" habitat conditions (with or without harvest) as well as for "Restoration" conditions. The latter incorporated potential improvements in key habitat features that could achieved over the next 30 years given "unlimited funding constrained by existing institutional factors such as infrastructure, water rights, etc." The sums across population units of these EDT projections are presented in Table 4 for the "Current no Harvest" and "Restoration" conditions. Because values for fall Chinook were for spawning populations both above and below Prosser, we multiplied them by 0.25 (25%), which is roughly the proportion of Yakima fall Chinook assumed to spawn above Prosser. Although we did not use the "Current no Harvest" EDT abundances, these were only slightly larger than the 15-yr geometric means that we examined (Table 3 and Table 4).

Table 3. Counts of adult returns at Prosser Dam.

Year	Spring Chinook	Fall Chinook	Coho	Steelhead
1982	1,822			
1983	1,441	380		1,140
1984	2,658	1,331		2,194
1985	4,560	273		2,235
1986	9,439	735	230	2,465
1987	4,443	536	83	2,840
1988	4,246	224	18	1,162
1989	4,914	670	291	814
1990	4,372	1,504	289	834
1991	2,906	971	269	2,265
1992	4,599	1,612	190	1,184
1993	3,917	1,065	165	554
1994	1,302	1,520	560	925
1995	666	1,322	725	505
1996	3,179	1,392	1,338	956
1997	2,993	1,120	1,312	1,069
1998	1,903	1,148	4,679	1,070
1999	2,781	1,768	3,943	1,380
2000	19,249	2,413	6,138	2,942
2001	23,256	4,285	5,034	4,525
2002	15,099	6,241	818	2,235
2003	6,957	4,841	2,353	2,139
2004	10,444	2,674	2,052	3,099
15-year Geom. Mean (1990-2004)	4,426	1,883	1,095	1,410

Table 4. EDT abundance projections for spring Chinook (American, Naches, and Upper Yakima populations), fall Chinook (Lower Yakima and Marion Drain populations), and coho salmon (American, Naches, and Upper Yakima populations).

Reference Condition	Spring Chinook	Fall Chinook	Coho
Current no Harvest	4,781	2,499	1,233
Restoration	7,860	3,406	2,256

3.5.2. *Frequency of "year types" and adult estimates*

We assumed two alternative futures with respect to the frequency of occurrence of each year type. The first mimicked historic conditions, and assumed that dry, wet, and average years would occur 25%, 25%, and 50% of the time, respectively. The second alternative assumed that flow conditions would worsen in the future, such that dry and average years would each occur 50% of the time (no wet years). It is probable that future years will be drier given current projections for the Yakima River (Mote et al. 2003; Leung et al. 2004; Payne et al. 2004). In addition, much of the flow available in the lower Yakima River is irrigation return flow. The long term trend for irrigation return flow is down (KID personal communication), indicating that even if there is not a climatic related decrease in runoff volume, changes in irrigation runoff volume may still result in decreasing flows in the lower Yakima River.

To calculate increases in adult returns for a given flow scenario, we first need to compute expected returns (R_P) for each year type i under baseline conditions. The average adult returns to Prosser can be partitioned by year type as follows:

(12) $$\overline{R}_P = \sum_i f_i * (R_P)_i = \sum_i f_i * (s_{P\text{-}M})_i * R_{s=1} ,$$

where f_i is the frequency of each year-type i, and $R_{s=1}$ is the number of returns to Prosser when $s_{P\text{-}M} = 1$ (i.e., when Prosser-to-McNary smolt survival is 100%). From equation (11), it follows that

(13) $$R_{s=1} = \text{Smolts}_P * \text{SAR}_{M\text{-}P} .$$

We are only interested in $R_{s=1}$ as a convenient way to compute R_P for each year type. By rearranging equation (12), $R_{s=1}$ is easily calculated given specified values for $\overline{R}_P$, f_i, and $(s_{P\text{-}M})_i$. Finally, adult returns to Prosser by year type are computed as $(R_P)_i = (s_{P\text{-}M})_i * R_{s=1}$.

Conceptually, all we have done is compute returns by year type given assumed constraints ($\overline{R}_P$ and f_i) and differences among year types in flow-based estimates of Prosser-to-McNary smolt survival ($s_{P\text{-}M}$). Intuitively, if survival rates are relatively low in dry years, then adult returns to Prosser will also be low. In addition, we computed adult returns (R_P) using only the "historic" frequencies for future year types (f = 0.25, 0.25, and 0.50 for wet, dry and average years, respectively). The resulting values of R_P for dry and average years were then used in the pessimistic case as well (f = 0.50 for both dry and average years).

The annual number of *additional* adults for a given flow scenario was computed as the weighted average across year types of adult returns multiplied by the proportional increase in smolts at McNary (equation 10):

(14) $$\text{Number of } \textit{additional} \text{ adults} = \sum_i f_i * (R_P)_i * [\text{Percent (\%) increase in smolts at McNary/100}]_i$$

Finally, the average annual percent increase in adult returns to Prosser was simply:

(15) $$\text{Percent (\%) increase in adults} = [(\text{Number of } \textit{additional} \text{ adults}) / \overline{R}_P\ ] \text{ X } 100 \ .$$

3.5.3. Model averaging

Adult estimates were computed for each of three forms of the flow-survival relationship (*flow*, *log(flow)*, and broken-stick forms) to explicitly show the implications of "model uncertainty" on adult estimates. However, the level of statistical support for each form differed depending on the species. To provide adult estimates that integrated across these forms, we used a simple approach based on AIC values called "model averaging" (Burnham and Anderson 2002). The relative support or "weight" (w_i) was computed for each form as follows:

(16) $$w_i = \frac{\exp[-0.5\Delta_i]}{\sum_{k=1}^{3}\exp[-0.5\Delta_k]} \ .$$

where Δ denotes the difference in AIC between each form and the form with the lowest AIC (for which $\Delta_i = 0$). The weights (w_i), which sum to one, can be interpreted as the probability that a given form is the "best" model based on AIC, given the data and set of candidate models. In our case, the set of candidate models was limited to just three: each alternative form of the flow-survival relationship with the full set of auxiliary variables selected during the model-selection phase. Finally, a single value for an adult estimate was computed as the weighted average of the estimates across the three forms, with weights equal to w_i.

3.5.4. Adult estimates for steelhead

Consistent with Steve Crochi's analysis, we assumed that flow-survival relationships for steelhead would most closely resemble those of spring Chinook (which share similar juvenile life-histories and timing of out-migration). This is a questionable assumption, and the results of the analysis may not reflect actual trends. As an example of potential benefits of flow increases for steelhead, we computed adult estimates based on model averaging results for spring Chinook, but using the 15-yr geometric mean for steelhead as the expected adult returns under baseline flow conditions (Table 3). We did not use EDT results because these analyses were done for combined populations of steelhead and resident rainbow trout.

4.0 Results

4.1. Spring Chinook

Our initial logistic regressions evaluated differences in survival rates among *release types*. When all four categories were modeled separately, this factor was highly significant ($P < 0.001$). However, the key difference was between hatchery and wild fish ($P < 0.001$); differences in survival rates between fish released at or near Prosser versus those released well above Prosser were minimal and not significant ($P = 0.09$). We therefore focus on results for analyses in which hatchery and wild fish were treated separately, with data from different locations (at or above Prosser) pooled for each *type* (hatchery and wild).

4.1.1. Data summary

There were a total of 381 observations (daily survival-rate estimates) for hatchery and wild release groups across the six years, corresponding to 276 unique days with at least one survival-rate estimate (Table 5). Observations were reasonably well distributed across each release type and year (Table 5).

Table 5. Number of daily survival-rate estimates by release type and year for release groups of 50 or more fish. Also shown is the number of unique days with at least one estimate.

Year	Hatchery	Wild	Total	Unique Days
1999	28	14	42	33
2000	46	25	71	48
2001	41	27	68	58
2002	37	14	51	38
2003	45	33	78	48
2004	44	27	71	51
Total	241	140	381	276

Figure 4 presents box plots of data corresponding to each year (release types combined) and to each release type (years combined). Median values for both survival-rate estimates and day of migration tended to decline across years from 1999 to 2004. Flows during migration were highest in 1999, the year with were highest survival rates. Flows were extremely low and temperatures high in 2001, though survival rates in 2001 were similar to those observed during 2002-2004. Hatchery release groups tended to have slightly lower survival rates and later migrations than did wild release groups (Figure 4).

Across years, there were clear patterns between the day of migration and other variables (Figure 5). In general, as the day of migration increased, survival rates and travel times decreased, while temperatures increased. Flows, on the other hand, showed more varied trends across days of migration depending on the year (Figure 5). There were no obvious differences in patterns between hatchery and wild release groups.

Figure 6 displays survival-rate estimates as a function of flow, log(flow), temperature and median travel time for each year. Survival rates tended to increase as flows and travel times increased, with the exception of 1999 (Figure 6). In contrast, survival rates generally decreased as temperature increased. Again, there were no obvious differences in patterns between hatchery and wild release groups.

It is clear from Figure 5 and Figure 6 that there is considerable correlation among potential explanatory variables, in particular among day of migration, temperature, and travel time.

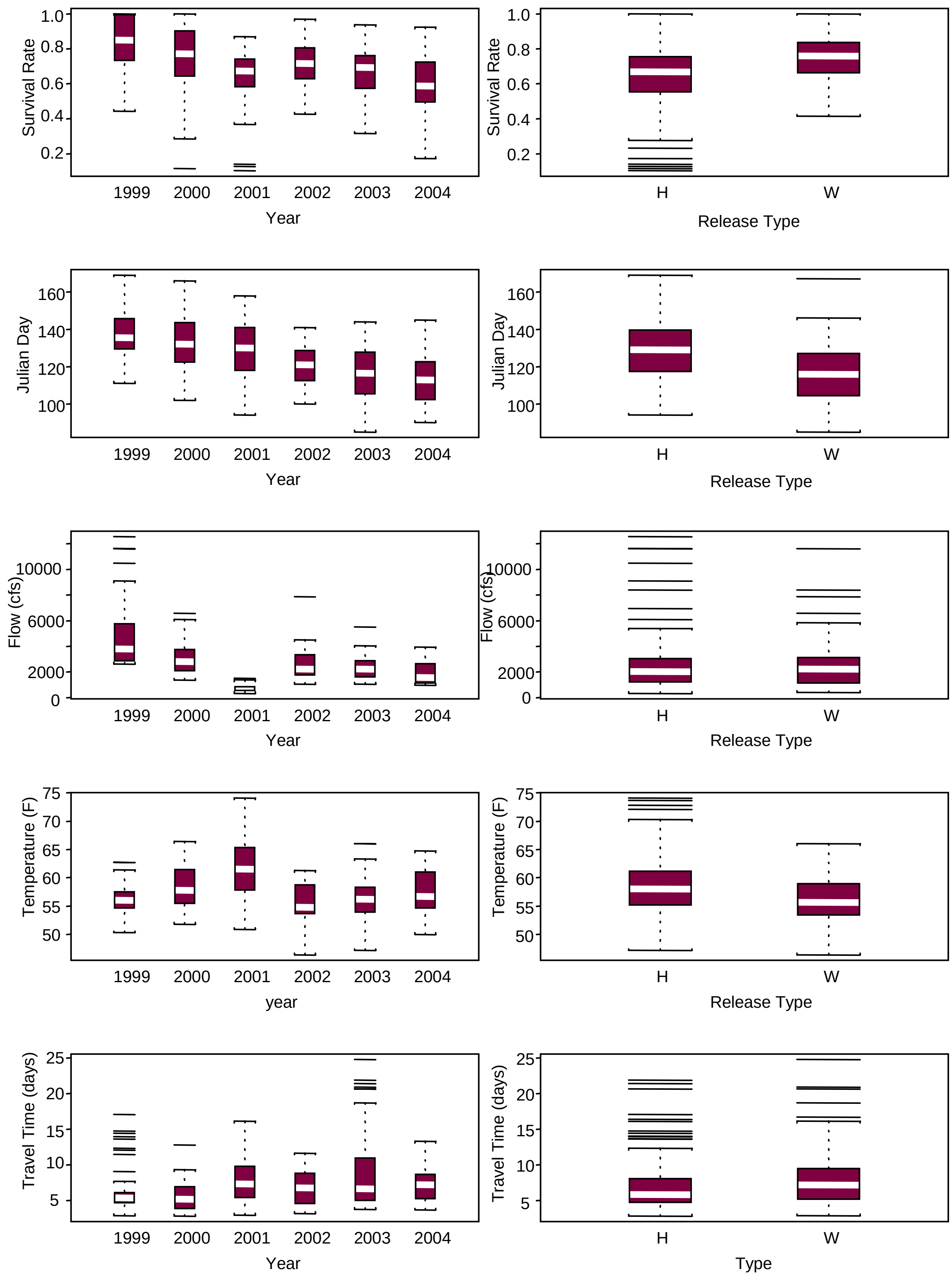


Figure 4. Box-plots of spring Chinook survival-rate estimates, migration day, flow, temperature, and median travel time for each year (across release types; left column) and for each release type (across years; right column). H = hatchery release groups and W = wild release groups.

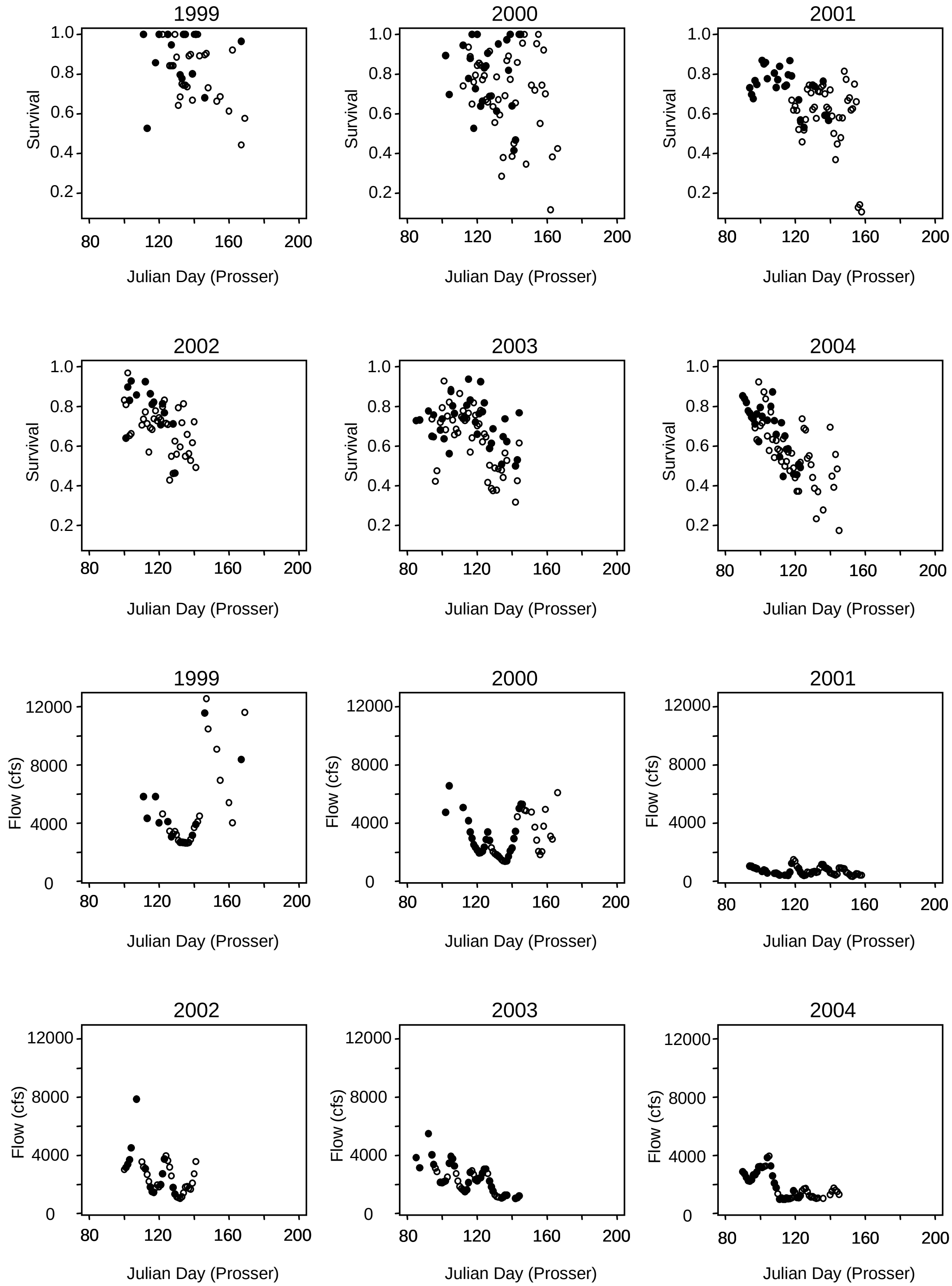


Figure 5. Spring Chinook survival-rate estimates, flows, temperatures, and median travel times as a function of migration day for each year. Open circles represent hatchery release groups; solid circles are wild release groups.

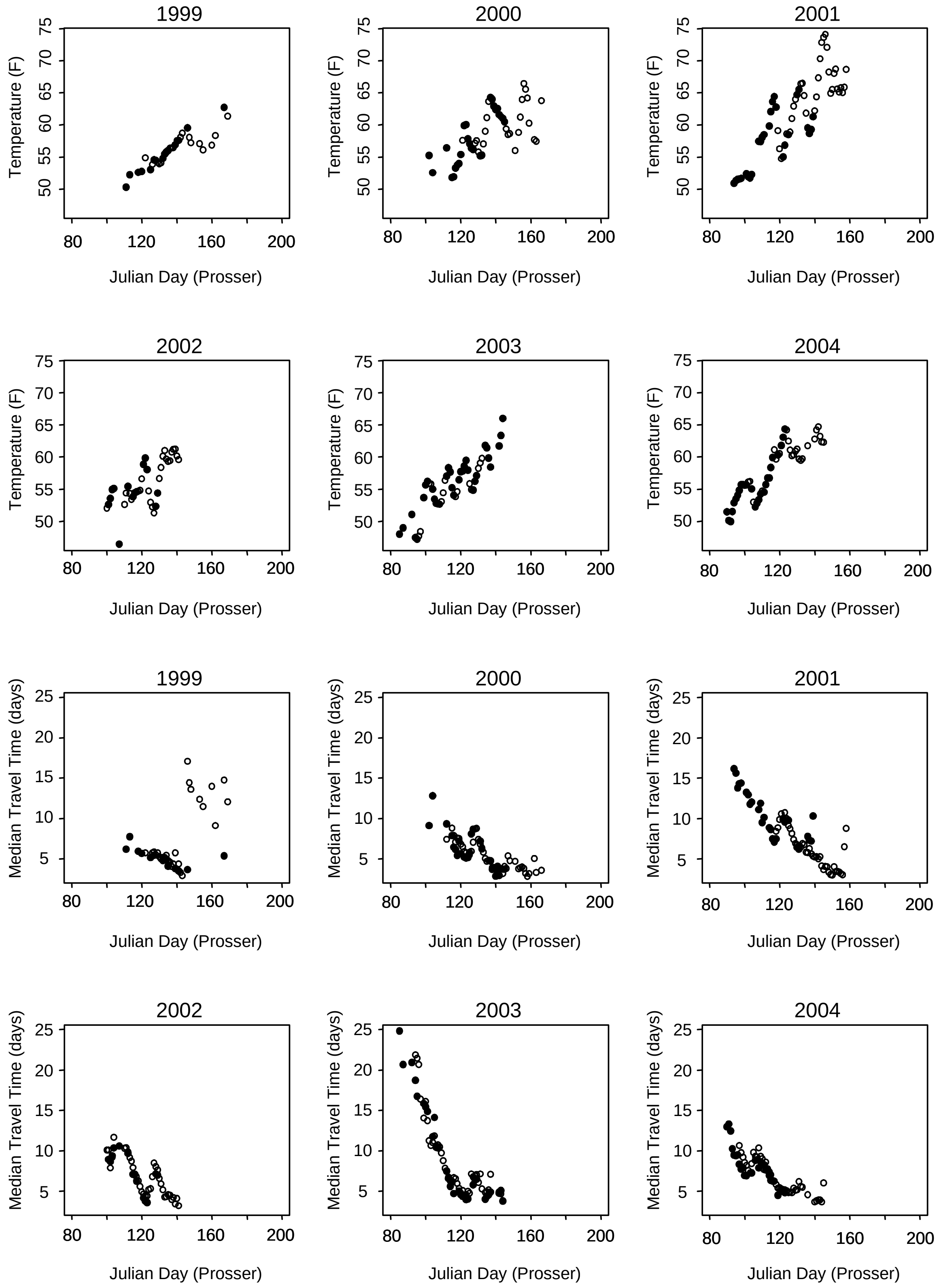


Figure 5. Continued.

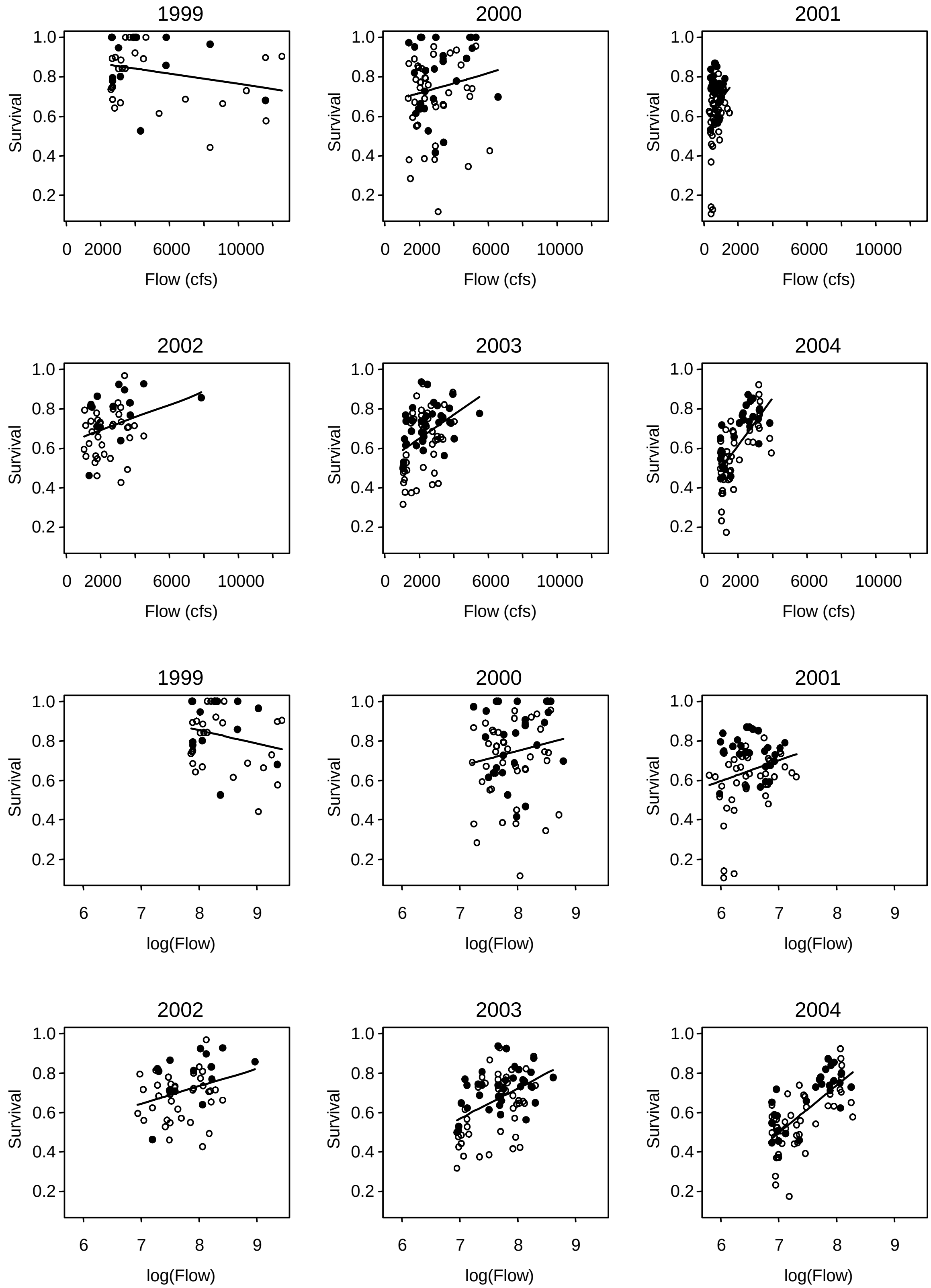


Figure 6. Spring Chinook survival-rate estimates as a function of flow, log(flow), temperature and median travel time by year. Open circles are hatchery release groups; solid circles are wild release groups.

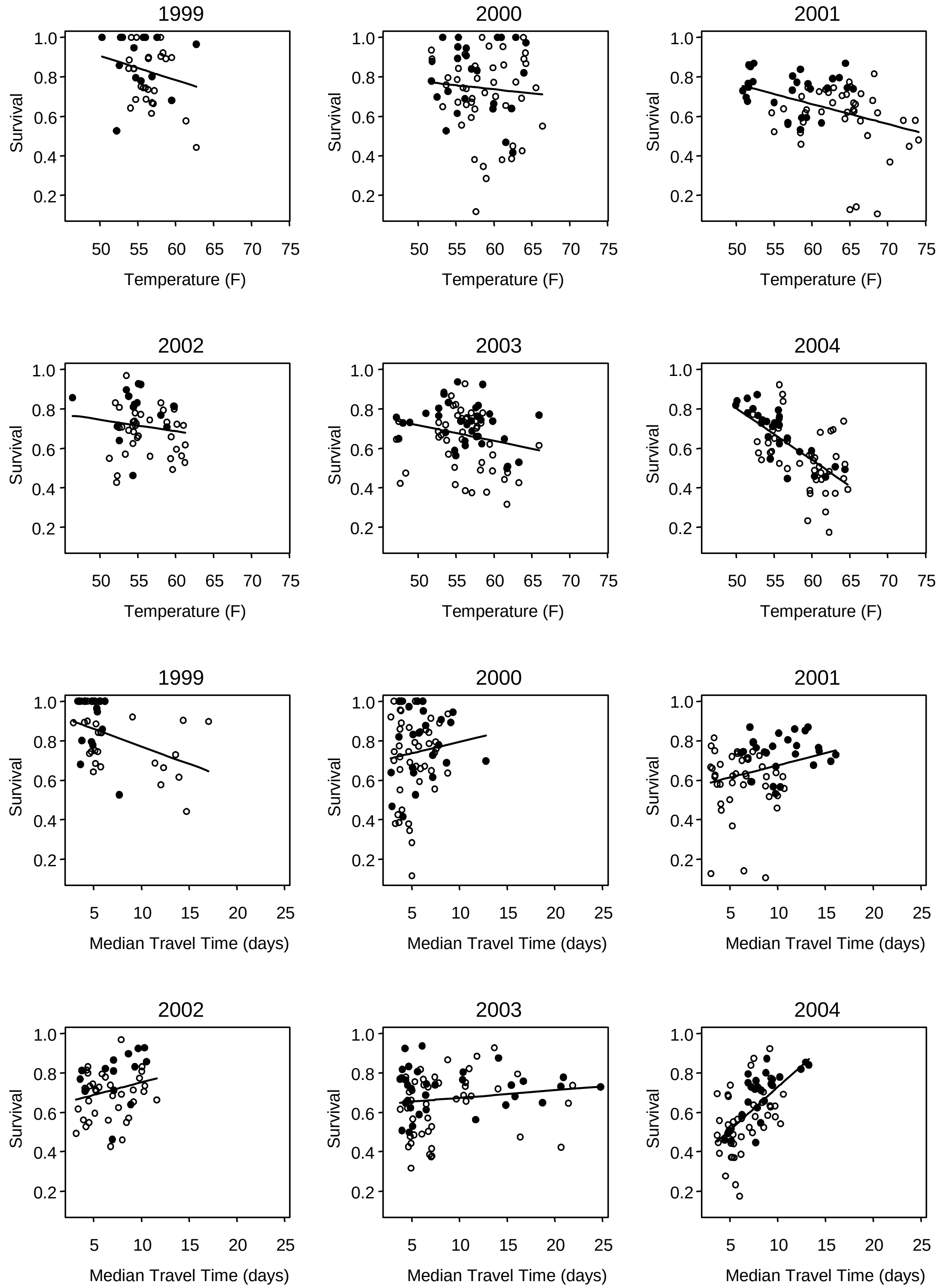


Figure 6. Continued.

4.1.2. Baseline logistic regression model

The “best” logistic model based on the stepwise regression procedure included the following explanatory variables, in the order they were selected: *year*, *migration day*, *travel time*, *release type* and *flow*. We refer to this model as the “baseline” model for spring Chinook. Model-selection based on AIC resulted in the same model. Note that *log(flow)* was also included as a candidate variable, but the linear form *flow* was preferred. A summary of the regression coefficients is provided in Table 6, and the analysis of deviance in Table 6. In addition, plots of the partial effects of each variable on logit(survival) are shown in Figure 7.

In brief, the dominant explanatory variable was *year*, suggesting that important differences in mean survival rate existed across years, and that these differences could not be attributed effectively to others variables such as flow or temperature. The coefficients further suggest a general decline in mean survival rates from 1999-2004 (Table 6; Figure 7). Next, *migration day* had an apparent negative effect on survival, that is, survival rates declined as the day of migration increased. Accounting for *year* and *migration day* then revealed an apparent negative effect of *travel time* on survival, suggesting that longer travel times were associated with reduced survival rates (Table 6; Figure 7). *Release type* also had a significant effect, with wild release groups experiencing slightly higher survival on average than hatchery release groups. Finally, the effect of *flow* implied that survival rates increased as flows increased (Table 6; Figure 7). Note that adding *temperature* to this model had virtually no effect (P = 0.68).

While all variables were highly significant, the full model accounted for only 1433.4 of the total deviance of 3514.8 (Table 7). As a result, the residual deviance (2081.5) was much greater than the residual degrees of freedom (371). (Ideally, the residual deviance of a fitted model will be similar in magnitude to the residual degrees of freedom.) Attributing this unexplained variation to over-dispersion yielded an estimate of the dispersion parameter of $\hat{\phi}$ = 5.38, and hence, the standard errors in Table 6 are roughly 2.3 (= sqrt[5.38]) times greater than those assuming no over-dispersion. Otherwise, no obvious problems were evident among standard diagnostic plots of residuals.

Figure 8A shows observed survival rates and the predicted flow-survival relationship across years and release types. This “average” relationship is nearly linear, and implies a relatively minor effect of flow on survival rates. In the following section, we examine alternative flow-survival relationships for spring Chinook and examine the sensitivity of these relationships.

Table 6. Regression coefficients and standard errors (SE) for the logistic model fit to 381 spring Chinook survival-rate estimates. Note that the coefficient for 1999 is taken to be zero, whereas coefficients for 2000-2004 represent differences in logit(survival) relative to 1999. Similarly, the coefficient for the hatchery *release type* is taken to be zero, and the coefficient shown is the relative difference in logit(survival) for wild release groups.

Variable	Coefficient	SE
Intercept	5.800	0.555
Year = 2000	-0.331	0.176
2001	-0.321	0.189
2002	-0.711	0.180
2003	-0.827	0.178
2004	-1.285	0.185
Migration day	-0.033	0.003
Travel time	-0.109	0.014
Release type = Wild	0.229	0.067
Flow	0.000204	0.000035

Table 7. Analysis of deviance for the logistic model fit to 381 spring Chinook survival-rate estimates. Df = degrees of freedom.

Variable	df	Deviance	Residual df	Residual deviance	F Value	P-value
Intercept	1		380	3514.8		
Year	5	545.2	375	2969.6	20.3	P < 0.001
Migration day	1	423.4	374	2546.3	78.7	P < 0.001
Travel time	1	200.1	373	2346.2	37.2	P < 0.001
Release type	1	66.5	372	2279.7	12.4	P < 0.001
Flow	1	198.2	371	2081.5	36.8	P < 0.001
Total	10	1433.4	371	2081.5		

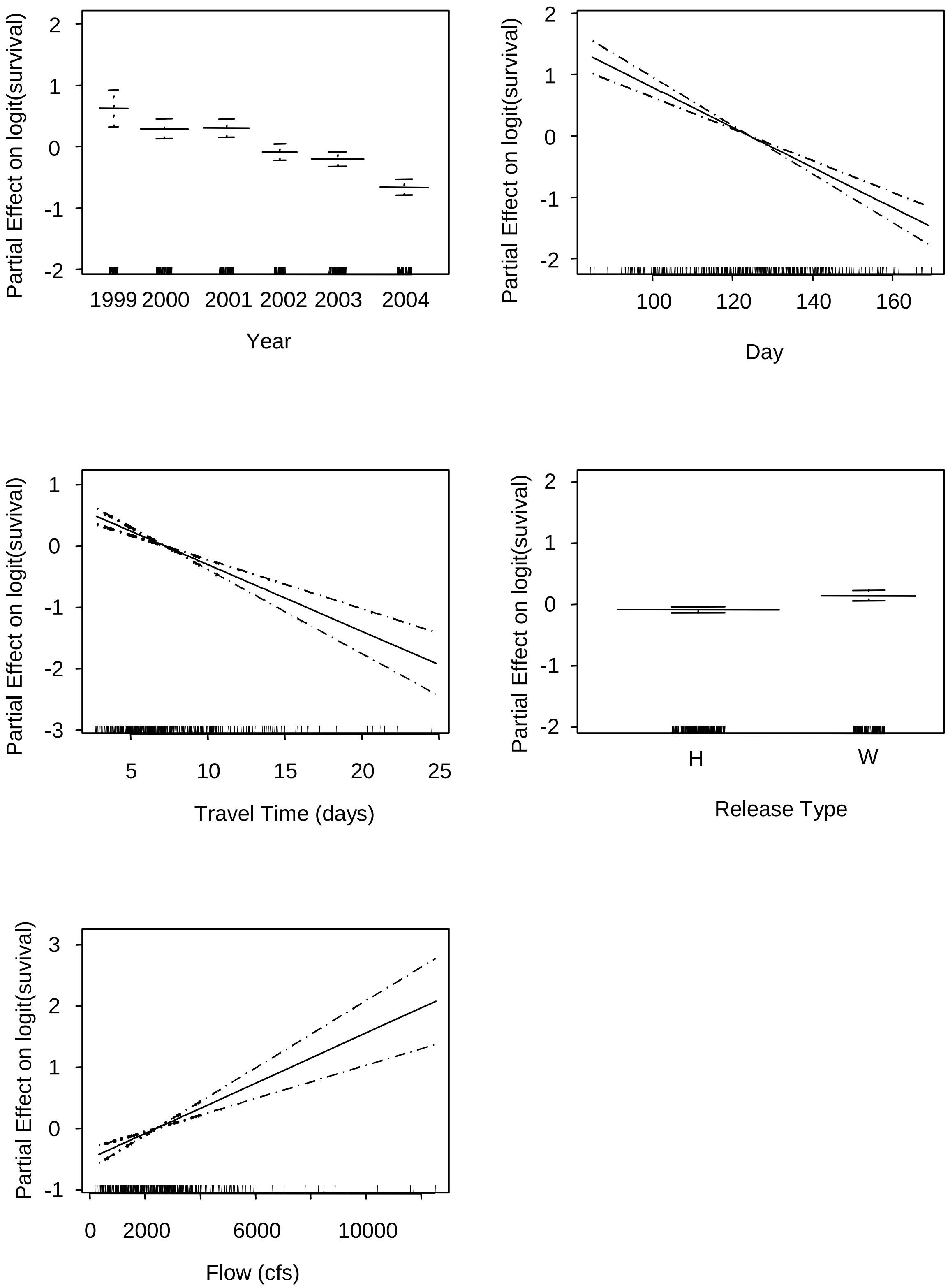
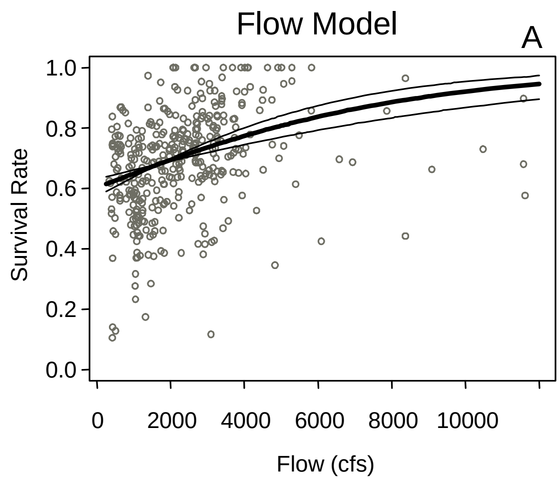
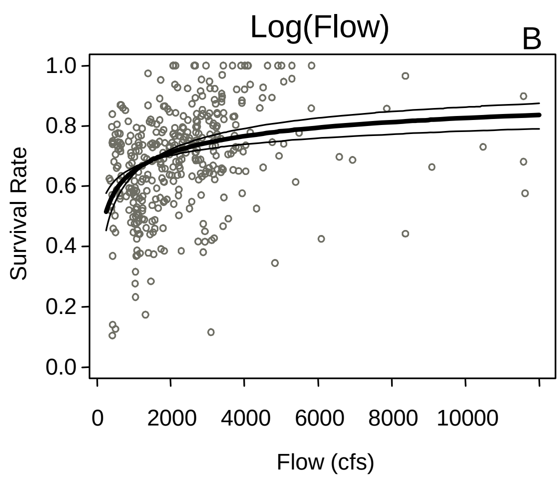


Figure 7. **Partial effects of *year*, *migration day*, *travel time*, *release type*, and *flow* on deviance residuals of logit(survival). Each plot has the same scale for the Y-axis so that the relative effect of each variable can be compared. Dashed lines indicate approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates for a given variable.**





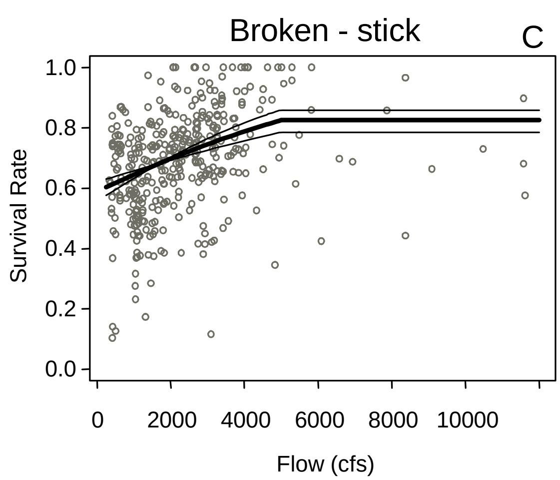


Figure 8. Predicted relationships (bold lines) between flow and survival rate across years and release types for (A) the *flow* model, (B) the *log(flow)* model, and (C) the broken-stick model. Open circles are the observed survival rates. Thin lines are approximate 95% confidence intervals for the flow-survival relationship.

4.1.3. Alternative flow-survival relationships

Regressions using the *log(flow)* or "broken-stick" forms of the flow-survival relationship performed well based on the AIC model-selection criterion. In addition, we found that flow-survival relationships were generally robust to the set of auxiliary variables (*year*, *migration day* etc.) included in the regressions. A summary of model results is provided in Table 8, where "Model 1" refers to the baseline model discussed in the previous section.

First, we used *log(flow)* instead of *flow* in the baseline model. The *log(flow)* form implied greater effects of flow on survival rates at low flows (Figure 8B). However, the difference in AIC for this model compared to the baseline *flow* model was 4.1 (Table 8, Model 6), indicating that the statistical support for *log(flow)* was somewhat weaker than for *flow*.

Evidence of non-linearity between *flow* and logit(survival) was further assessed using a generalized additive model (GAM), in which the flow effect was modeled using a smoothing spline (Figure 9). The fit provided moderate evidence for a non-linear relationship (approximate P = 0.051) (compare Figure 9 with Figure 7E). However, in contrast to the strongly curved relationship assumed by *log(flow)*, the GAM relationship appeared somewhat linear at low flows, with a potential plateau (breakpoint) at roughly 5000 cfs.

We therefore fit a broken-stick model with a breakpoint at 5000 cfs. The AIC for this model was only slightly greater than that for the baseline *flow* model (Δ_i = 0.2; Table 8, Model 11), indicating that both models had very similar statistical support. The broken-stick form had a slightly larger flow coefficient (Table 8, Model 11 versus Model 1), and hence, predicted a slightly greater effect of flow on survival for flows less than 5000 cfs (Figure 8).

To asses the sensitivity of flow-survival relationships to the presence of other variables, we removed each auxiliary variable one at a time, beginning with the last variable entered (Table 8). Regression fits deteriorated considerably with each removal (i.e., values of residual deviance and AIC showed large increases), but the flow coefficients remained similar regardless of model form. The most obvious differences in coefficients were for models with only *year* and *day* (Table 8, Models 3, 8, and 13). These models implied lower effects of flow on survival. Nevertheless, the predicted flow-survival relationships changed very little across the various models, as illustrated in Figure 10.

Table 8. Flow coefficients and AIC values (Δ*i*; differences from Model 1, the baseline model) for three alternative forms for the flow-survival relationship: the *flow*, *log(flow)*, and broken-stick forms. For each form, results are shown for the full model and models with each auxiliary variable removed one at a time. *K* is the number of parameters in a model. All AIC values were computed using the dispersion-parameter estimate for the baseline model (ϕ = 5.38).

Model	Form	Auxiliary variables	Flow Coefficient	Standard error	Residual Deviance	*K*	AIC (Δ_i)
1	Flow	Year+Day+Travel+Type	0.00020	0.00003	2081.5	10	0.0
2		Year+Day+Travel	0.00020	0.00003	2145.7	9	9.9
3		Year+Day	0.00013	0.00004	2457.5	8	65.9
4		Year	0.00020	0.00004	2767.3	7	121.5
5		None	0.00022	0.00003	3002.3	2	155.2
6	log(Flow)	Year+Day+Travel+Type	0.41	0.07	2103.7	10	4.1
7		Year+Day+Travel	0.39	0.07	2183.9	9	17.0
8		Year+Day	0.31	0.07	2437.8	8	62.2
9		Year	0.46	0.08	2714.4	7	111.6
10		None	0.37	0.05	3027.6	2	159.9
11	Broken-stick	Year+Day+Travel+Type	0.00024	0.00004	2071.9	11	0.2
12		Year+Day+Travel	0.00024	0.00004	2140.4	10	10.9
13		Year+Day	0.00018	0.00004	2425.2	9	61.9
14		Year	0.00025	0.00004	2699.6	8	110.9
15		None	0.00025	0.00003	2944.9	3	146.5

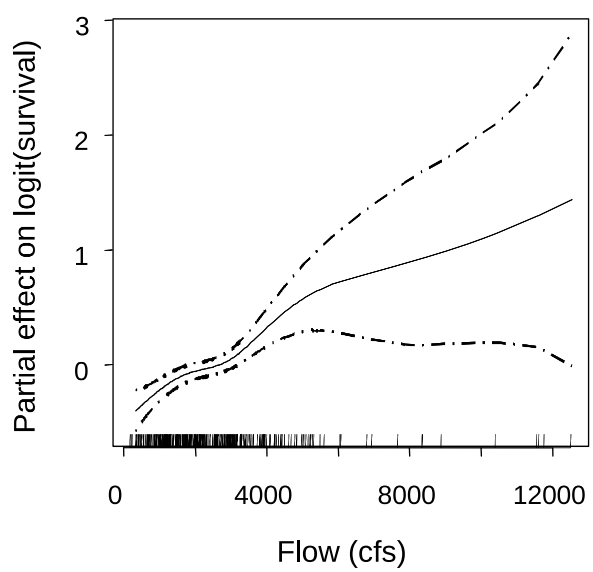


Figure 9. Partial effect of flow on logit(survival) estimated from a GAM model (i.e., the baseline model with flow modeled using a smoothing spline). Dashed lines indicate approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates.

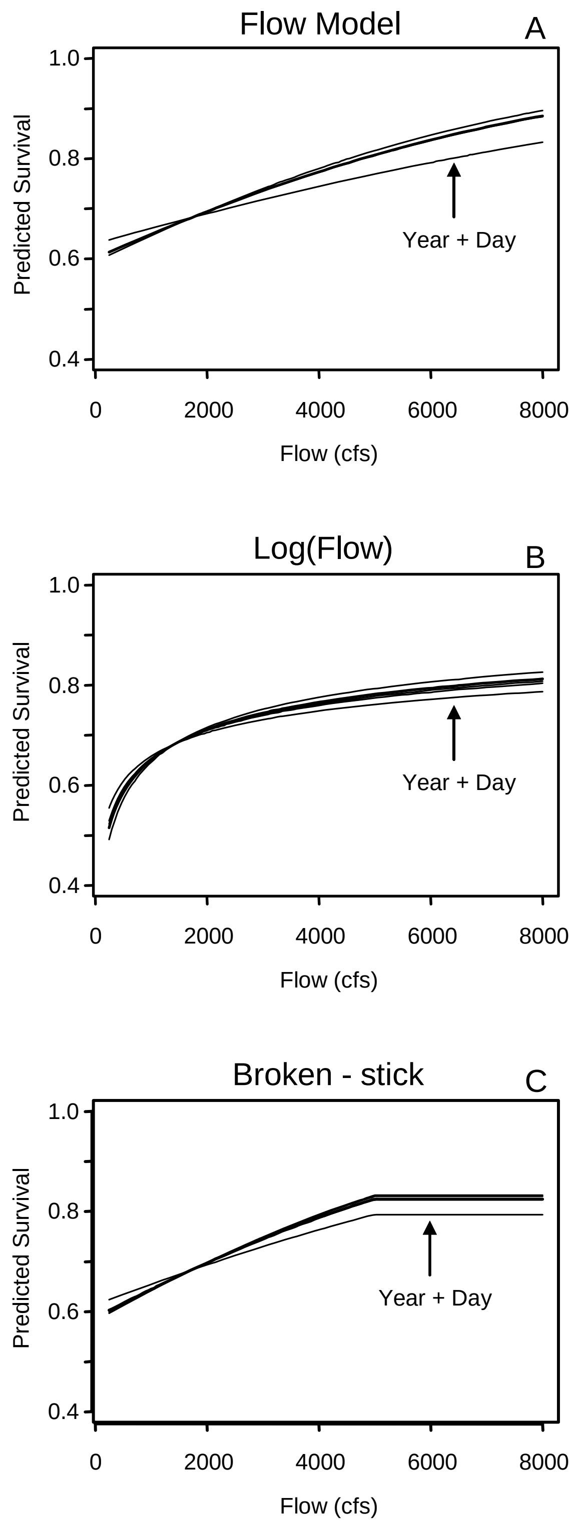


Figure 10. **Effect of removing auxiliary variables on the predicted flow-survival relationships for** (A) **the** ***flow*** **model (Table 5, Models 1-5),** (B) **the** ***log(flow)*** **model (Models 6-10), and** (C) **the broken-stick model (Models 11-15). Bold lines are the full models (Models 1, 5, and 10). Thin lines represent models with variables removed; in most cases these are indistinguishable from the full models with the exception of those with only** ***year*** **and** ***migration day*****.**

4.1.4. *Effects of flow increases on smolt abundance*

Potential benefits of flow increases on smolt abundance were estimated using coefficients for the *flow*, *log(flow)*, and Broken-stick models (Table 8, Models 1, 6 and 11). We examined all three forms because each model provided a reasonable fit to the data based on AIC, though *log(flow)* had the least support (Table 8).

Estimates of the percent increase in the number of smolts surviving to McNary are shown for each of the seven scenarios in Table 9 and Figure 11. Estimates were very similar for the *flow* and Broken-stick models, and ranged from roughly 2% to 6% for both the average year (2003) and dry year (2001), depending on the scenario. For the wet year (1999), increases in smolt abundance were estimated to be less than 2% for all scenarios. In comparison, estimates for the *log(flow)* model were lower for both the average and wet years, but substantially higher for the dry year (5% to 10%).

Table 9. Estimates of the percent (%) increase in the number of spring Chinook smolts surviving to McNary as a result of anticipated flow increases for each alternative flow scenario. Ranges in brackets are approximate 95% prediction intervals based on intervals for flow coefficients.

Flow	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	0.9 (0.6 - 1.1)	2.2 (1.4 - 2.8)	2.1 (1.4 - 2.9)
3a	1.2 (0.8 - 1.6)	3.0 (2.0 - 3.9)	3.0 (1.9 - 4.0)
3b	1.6 (1.1 - 2.0)	3.8 (2.5 - 4.9)	3.8 (2.4 - 5.1)
3c	1.3 (0.9 - 1.7)	3.2 (2.2 - 4.2)	3.2 (2.1 - 4.3)
3d	1.6 (1.1 - 2.1)	4.0 (2.7 - 5.2)	4.0 (2.6 - 5.5)
4a	2.0 (1.4 - 2.5)	4.8 (3.2 - 6.3)	4.9 (3.2 - 6.6)
4b	2.1 (1.4 - 2.6)	5.1 (3.4 - 6.6)	5.1 (3.3 - 6.9)
Log(flow)	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	0.5 (0.3 - 0.7)	1.6 (1.0 - 2.2)	5.0 (3.0 - 6.9)
3a	0.6 (0.4 - 0.9)	2.2 (1.3 - 2.9)	6.5 (4.0 - 9.1)
3b	0.8 (0.5 - 1.1)	2.7 (1.7 - 3.6)	7.8 (4.8 - 10.9)
3c	0.7 (0.4 - 1.0)	2.3 (1.4 - 3.2)	6.9 (4.2 - 9.6)
3d	0.8 (0.5 - 1.2)	2.8 (1.7 - 3.8)	8.2 (5.0 - 11.3)
4a	1.0 (0.6 - 1.4)	3.3 (2.1 - 4.5)	9.4 (5.7 - 12.9)
4b	1.1 (0.6 - 1.4)	3.4 (2.1 - 4.7)	9.7 (5.9 - 13.3)
Broken-stick	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	0.8 (0.5 - 1.0)	2.3 (1.6 - 3.0)	2.4 (1.6 - 3.2)
3a	1.0 (0.7 - 1.4)	3.2 (2.2 - 4.2)	3.3 (2.2 - 4.5)
3b	1.3 (0.8 - 1.7)	4.1 (2.8 - 5.2)	4.3 (2.8 - 5.7)
3c	1.1 (0.7 - 1.5)	3.5 (2.4 - 4.5)	3.6 (2.4 - 4.8)
3d	1.4 (0.9 - 1.8)	4.3 (2.9 - 5.5)	4.6 (3.0 - 6.1)
4a	1.6 (1.1 - 2.1)	5.2 (3.5 - 6.6)	5.5 (3.6 - 7.4)
4b	1.7 (1.1 - 2.2)	5.4 (3.7 - 6.9)	5.8 (3.8 - 7.7)

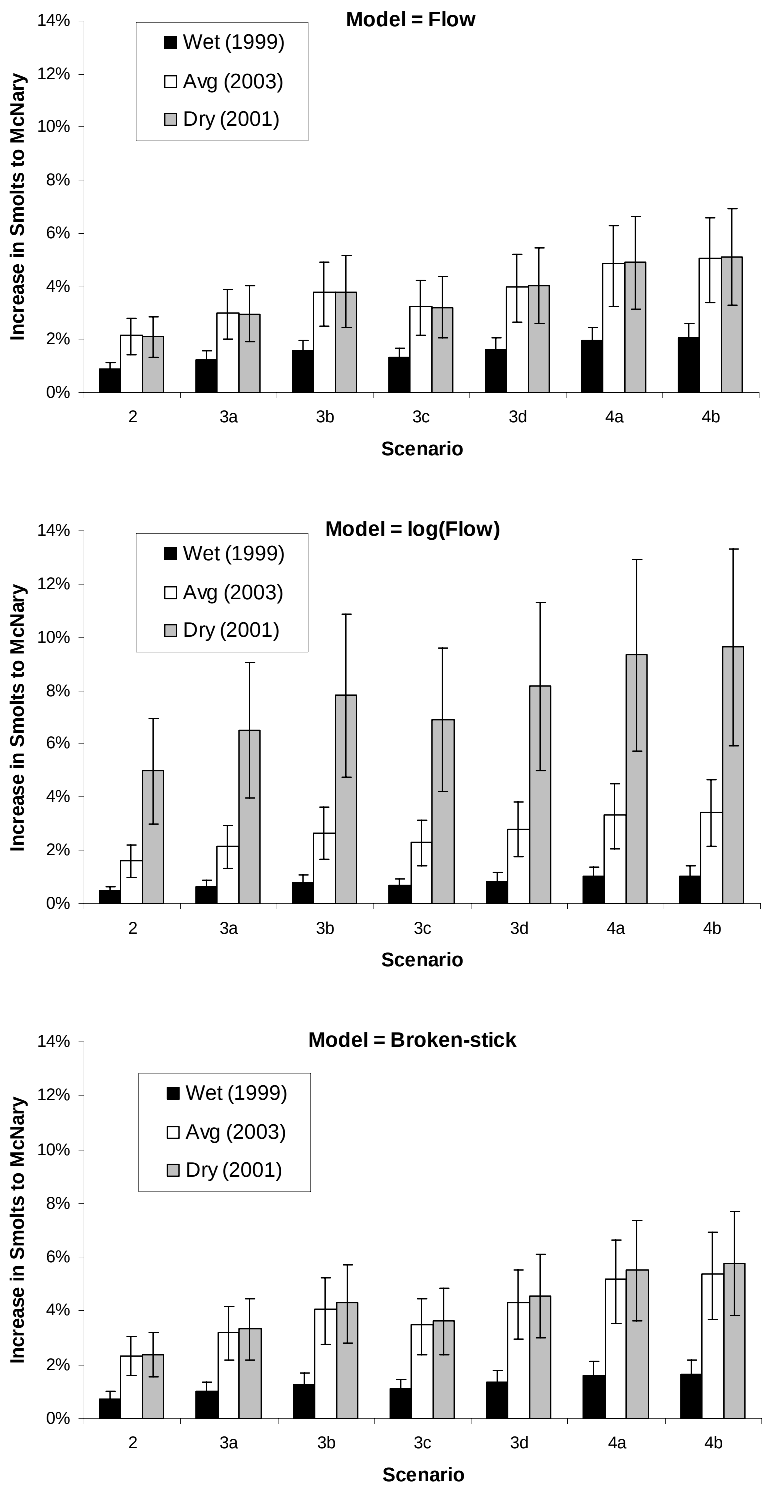


Figure 11. Estimates of the percent increase in the number of spring Chinook smolts surviving to McNary as a result of anticipated flow increases for each flow scenario. Error bars indicate approximate 95% prediction intervals based on intervals for flow coefficients.

4.1.5. Effects of flow increases on adult returns

Estimates of average annual increases in adult returns for spring Chinook were relatively low across flow scenarios. Adult estimates based on “model averaging” are shown in Table 10, while estimates for each form of the flow-survival relationship are shown in Table 11. The AIC weights (w_i) used in model averaging were equal to 0.50, 0.06, and 0.44 for the *flow*, *log(flow)*, and broken-stick forms, respectively. Again, this emphasizes that the *flow* and broken-stick forms had similar statistical support, while support for *log(flow)* was much weaker.

For model averaging, estimates of proportional increases in adult returns ranged from roughly 2% to 5%, depending on the scenario (Table 10). Numeric increases were generally less than 200 adults when based on an expected return equal to the recent 15-year geometric mean, and less than 400 adults for the EDT Restoration abundance (Table 10). Increases in adults were only marginally greater under the pessimistic assumption that future flow conditions would be characterized by 50% dry years and 50% average years (denoted “50/50” in Table 10). Note that values of expected abundance (*N*) for the “50/50” cases were lower than those for the “historic” frequency of year types (“25/25/50”, or 25% wet, 25% dry, and 50% average years) because estimates of survival rates from Prosser to McNary were lower for the “dry” year than for the omitted “wet” year.

Estimates specific to each flow-survival relationship depict the uncertainty in adult estimates due to uncertainty in the smolt-survival relationships (Table 11). In general, however, estimates were reasonably consistent across the different flow-survival relationships and similar to those obtained using model averaging.

Table 10. Estimates of average annual increases in spring Chinook adult returns based on “model averaging.” Results are shown for each flow scenario and two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). N = expected annual abundance (geometric mean) given unadjusted flow conditions.

	Percent (%) increase		Numeric increase based on 15-yr mean		Numeric increase based on EDT Restoration	
Scenario	25/25/50	50/50	25/25/50 (N = 4,426)	50/50 (N = 4,104)	25/25/50 (N = 7,860)	50/50 (N = 7,289)
2	1.8	2.3	81	94	144	168
3a	2.5	3.2	112	131	200	233
3b	3.2	4.0	142	166	252	295
3c	2.7	3.4	121	141	215	251
3d	3.4	4.3	150	176	267	312
4a	4.1	5.2	181	212	322	377
4b	4.3	5.4	189	222	336	394

Table 11. Estimates of average annual increases in spring Chinook adult abundance for each flow scenario and flow-survival relationship (*flow*, *log(flow)*, and broken-stick forms). Results are shown for two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). Ranges in brackets are approximate 95% prediction intervals based on smolt estimates. N = expected annual abundance (geometric mean) given unadjusted flow conditions.

Flow	Percent (%) increase		Numeric increase based on 15-yr mean (N = 4,426)		Numeric increase based on EDT Restoration (N = 7,860)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 4,089)	25/25/50	50/50 (N = 7,277)
2	1.8 (1.2 - 2.3)	2.1 (1.4 - 2.8)	78 (52 - 103)	87 (57 - 116)	139 (92 - 183)	155 (102 - 206)
3a	2.5 (1.6 - 3.2)	3.0 (2.0 - 3.9)	109 (72 - 143)	122 (80 - 162)	194 (128 - 254)	217 (142 - 287)
3b	3.1 (2.1 - 4.1)	3.8 (2.5 - 5.0)	138 (92 - 181)	155 (102 - 205)	245 (163 - 321)	275 (181 - 364)
3c	2.7 (1.8 - 3.5)	3.2 (2.1 - 4.3)	118 (78 - 154)	132 (86 - 174)	209 (139 - 274)	234 (153 - 310)
3d	3.3 (2.2 - 4.3)	4.0 (2.6 - 5.3)	147 (97 - 192)	164 (108 - 218)	260 (173 - 341)	292 (192 - 387)
4a	4.0 (2.7 - 5.2)	4.9 (3.2 - 6.4)	177 (118 - 231)	199 (131 - 263)	315 (210 - 411)	354 (233 - 467)
4b	4.2 (2.8 - 5.5)	5.1 (3.4 - 6.7)	186 (124 - 242)	209 (138 - 275)	330 (220 - 430)	371 (244 - 489)

Log(Flow)	Percent (%) increase		Numeric increase based on 15-yr mean (N = 4,426)		Numeric increase based on EDT Restoration (N = 7,860)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 4,109)	25/25/50	50/50 (N = 7,296)
2	2.0 (1.2 - 2.8)	3.2 (2.0 - 4.4)	89 (55 - 123)	132 (81 - 183)	159 (97 - 219)	235 (144 - 325)
3a	2.7 (1.6 - 3.7)	4.3 (2.6 - 5.8)	119 (73 - 163)	175 (107 - 240)	211 (129 - 289)	310 (190 - 426)
3b	3.3 (2.0 - 4.5)	5.1 (3.2 - 7.1)	144 (89 - 198)	211 (130 - 290)	256 (158 - 351)	375 (231 - 515)
3c	2.9 (1.8 - 3.9)	4.5 (2.8 - 6.2)	126 (78 - 173)	186 (114 - 255)	225 (138 - 308)	330 (202 - 453)
3d	3.4 (2.1 - 4.7)	5.4 (3.3 - 7.4)	152 (93 - 208)	221 (136 - 303)	269 (166 - 369)	393 (242 - 539)
4a	4.0 (2.5 - 5.4)	6.2 (3.8 - 8.5)	176 (109 - 240)	255 (158 - 349)	312 (193 - 427)	453 (280 - 620)
4b	4.1 (2.5 - 5.6)	6.4 (4.0 - 8.8)	182 (113 - 249)	264 (163 - 361)	323 (200 - 442)	468 (289 - 640)

Broken-stick	Percent (%) increase		Numeric increase based on 15-yr mean (N = 4,426)		Numeric increase based on EDT Restoration (N = 7,860)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 4,111)	25/25/50	50/50 (N = 7,301)
2	1.9 (1.3 - 2.5)	2.4 (1.6 - 3.1)	83 (56 - 109)	97 (65 - 128)	148 (99 - 194)	173 (116 - 227)
3a	2.6 (1.8 - 3.4)	3.3 (2.2 - 4.3)	115 (78 - 151)	135 (91 - 178)	205 (138 - 268)	240 (161 - 315)
3b	3.3 (2.2 - 4.3)	4.2 (2.8 - 5.5)	146 (98 - 191)	172 (115 - 225)	259 (174 - 339)	305 (205 - 400)
3c	2.8 (1.9 - 3.7)	3.5 (2.4 - 4.7)	124 (84 - 163)	146 (98 - 192)	221 (149 - 289)	259 (174 - 340)
3d	3.5 (2.4 - 4.6)	4.4 (3.0 - 5.8)	155 (104 - 202)	182 (123 - 239)	275 (185 - 359)	324 (218 - 424)
4a	4.2 (2.8 - 5.5)	5.4 (3.6 - 7.0)	186 (126 - 242)	220 (148 - 288)	330 (223 - 430)	391 (263 - 511)
4b	4.4 (3.0 - 5.7)	5.6 (3.8 - 7.3)	194 (132 - 253)	230 (155 - 300)	345 (234 - 449)	409 (276 - 534)

4.2. Fall Chinook

4.2.1. Data summary

There was little replication in survival-rate estimates for fall Chinook to adequately evaluate different release types. In a given year, release groups of sufficient size (25 of more fish) were predominantly of one release type only, providing little contrast needed to estimate potential differences among release types. Furthermore, the variable *release type* was not significant (P = 0.20) in the preliminary regression. We therefore focus on results for analyses in which data were pooled across all release types to estimate survival rates. A total of 66 observations were available across years (Table 12).

Table 12. Number of daily survival-rate estimates for fall Chinook smolts for release groups of 25 or more fish.

Year	All Types
1998	11
1999	18
2000	3
2001	13
2003	6
2004	15
Total	66

Survival rates and migration conditions varied considerably across release groups and years (Figure 12, Figure 13, and Figure 14). Survival rates and travel times were generally high in 1999, which featured high flows and low temperatures (Figure 12). In contrast, low survival rates were observed in 2004, during which flows were relatively low. However, survival rates were moderate in 2001, where flows were extremely low (Figure 12).

As for spring Chinook, there was considerable correlation among conditions that could potentially confound interpretation of results. For example, low survival rates were observed for four release groups with late migrations in 1998, which corresponded to days with relatively low flows and high temperatures (Figure 13 and Figure 14).

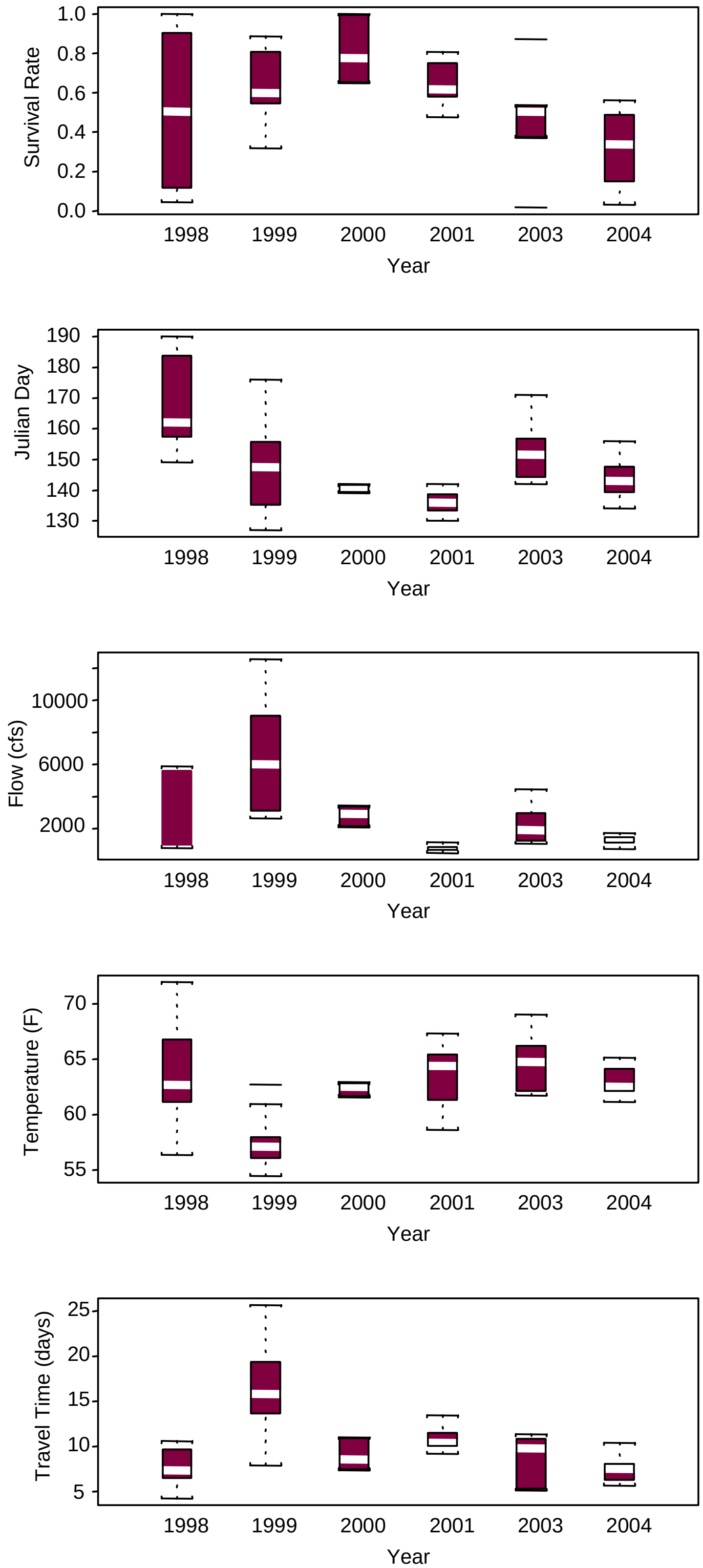


Figure 12. Box-plots of fall Chinook survival-rate estimates, migration day, flow, temperature, and median travel time for each year.

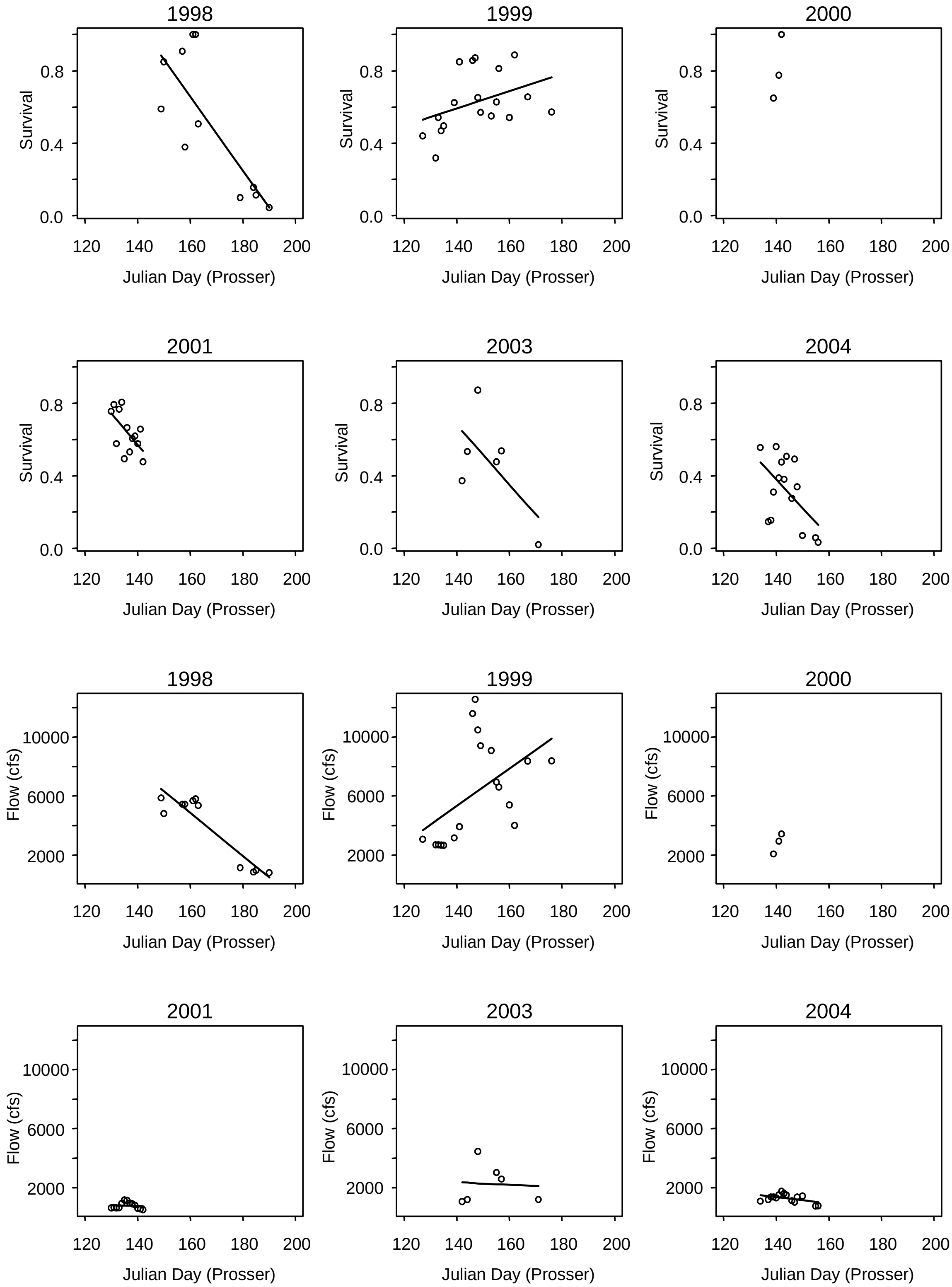


Figure 13. Fall Chinook survival-rate estimates, flows, temperatures, and median travel times as a function of migration day for each year.

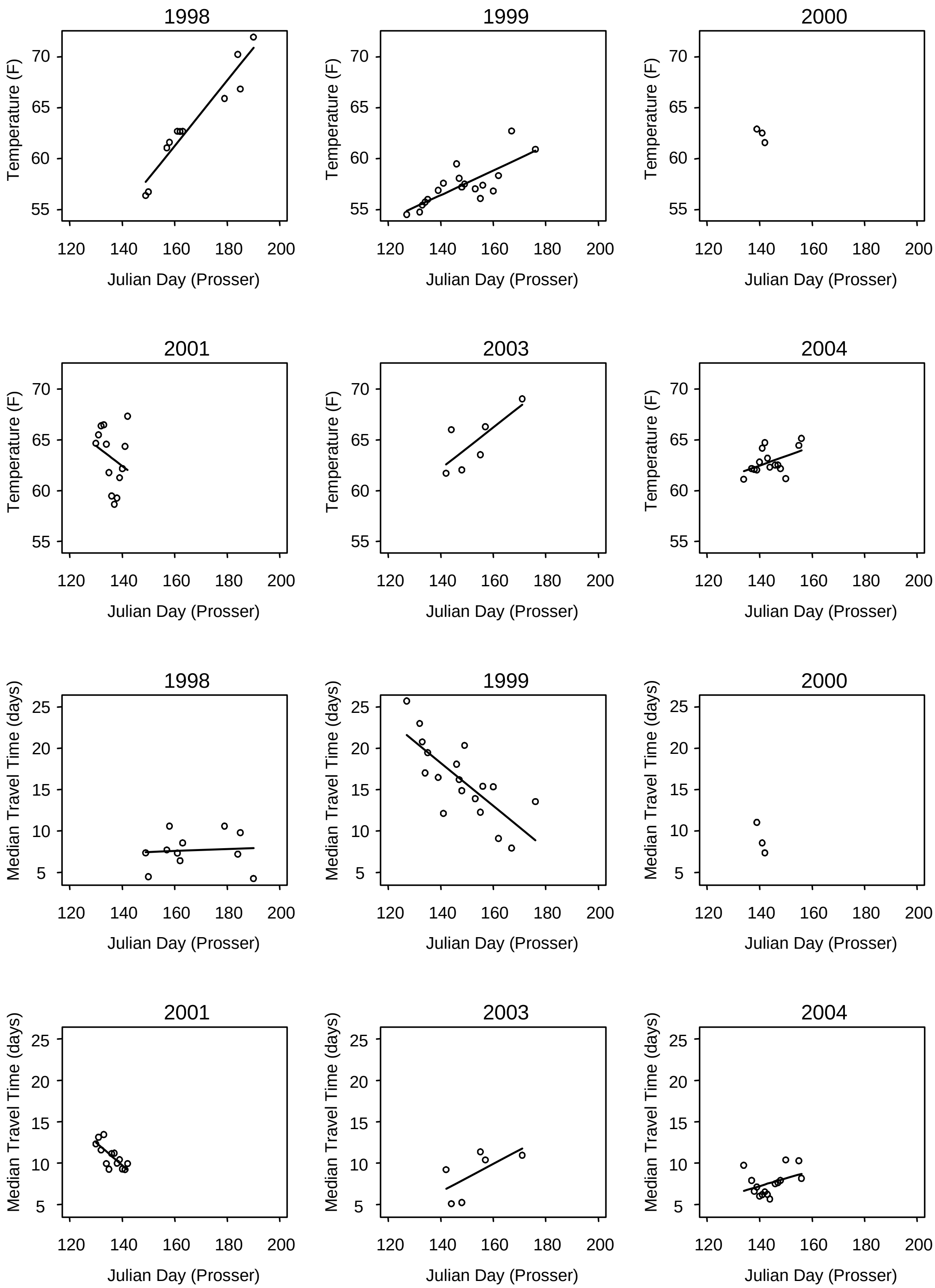


Figure 13. Continued.

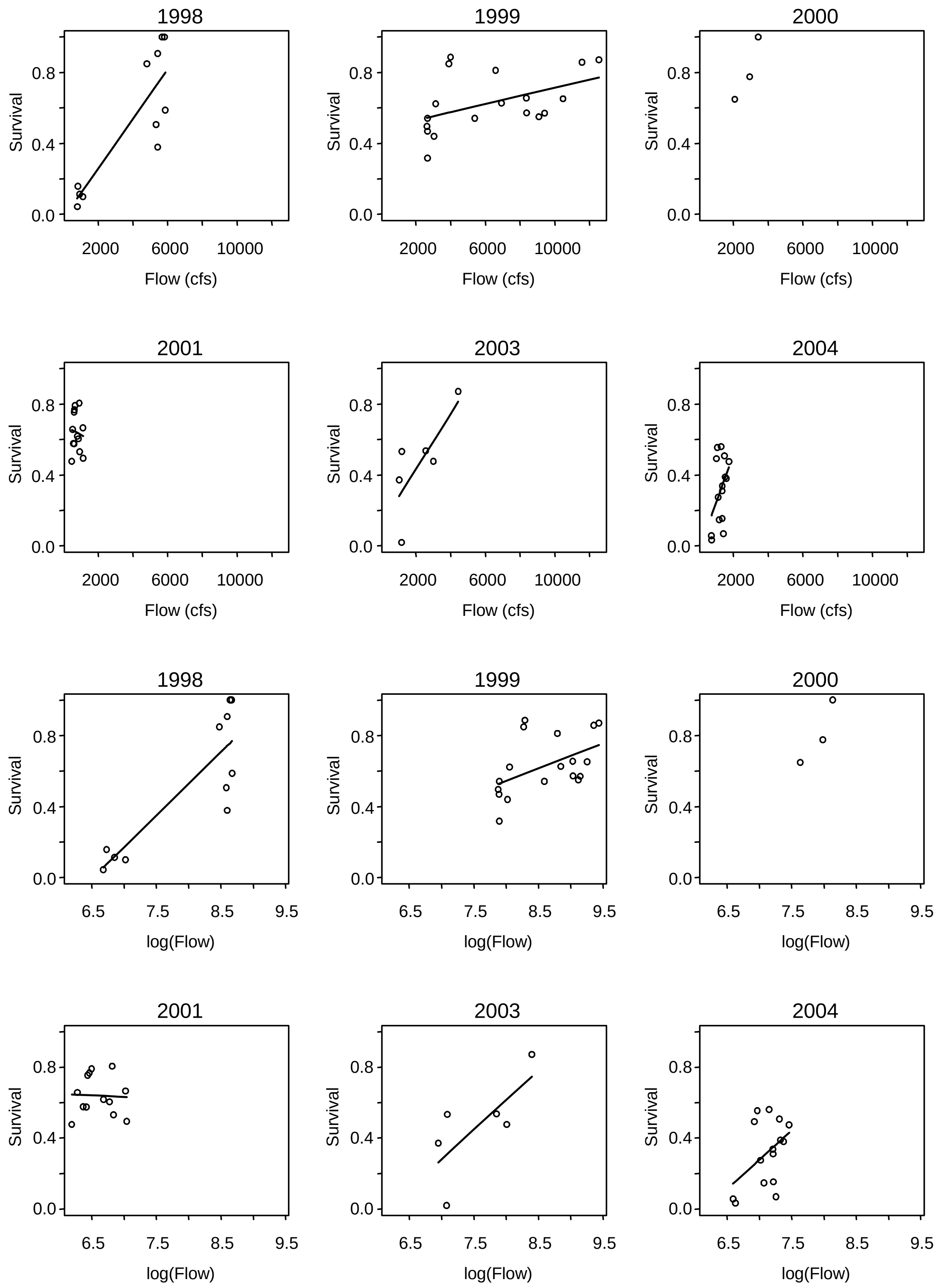


Figure 14. Fall Chinook survival-rate estimates as a function of flow, log(flow), temperature and median travel time for each year.

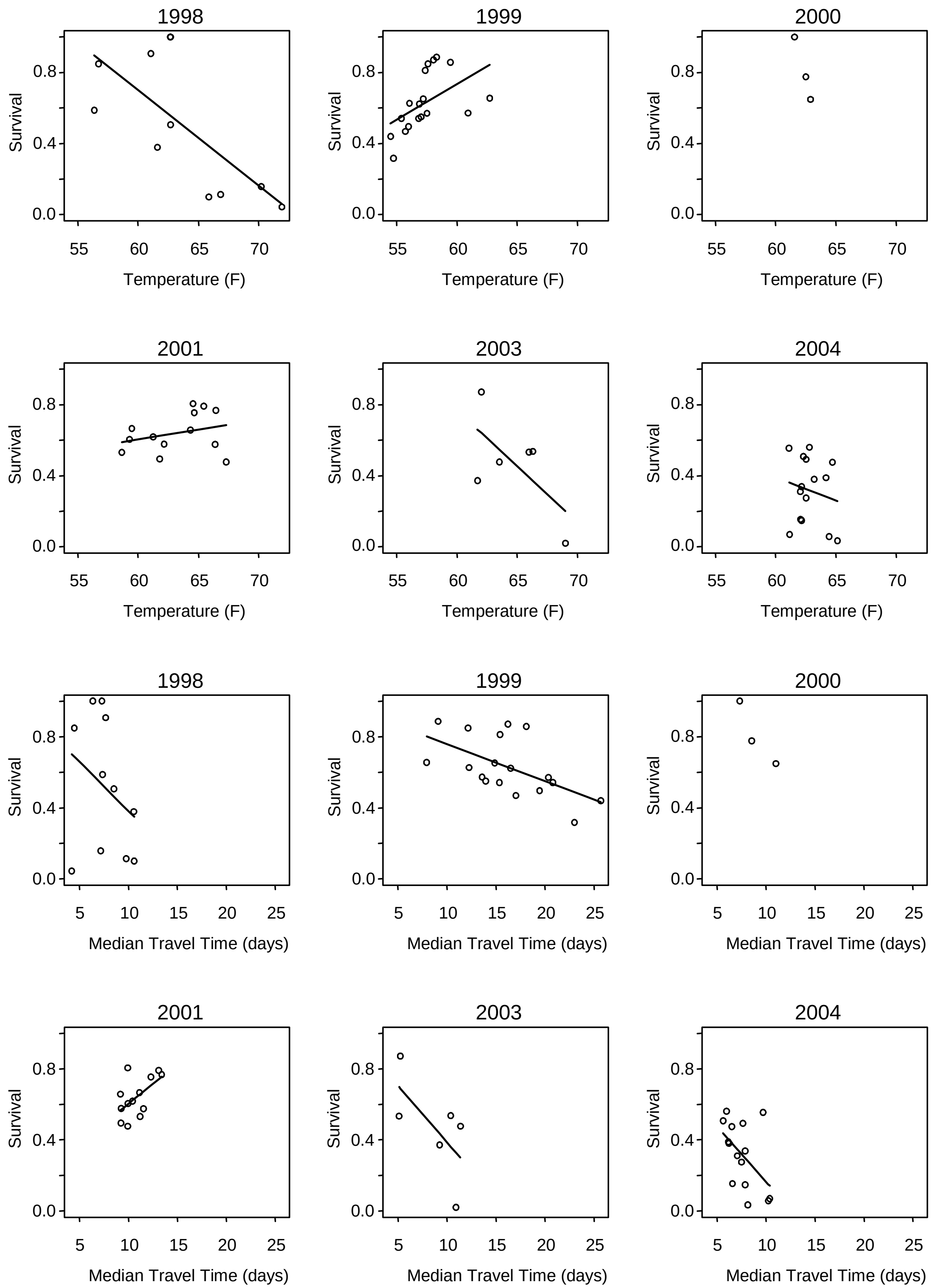


Figure 14. Continued.

4.2.2. Baseline logistic regression model

The “best” logistic model for fall Chinook included the variables *year*, *log(flow)*, *migration day* and *travel time*. A summary of the regression coefficients for this baseline model is provided in Table 13, and the analysis of deviance in Table 14. Plots of the partial effects of each variable on logit(survival) are shown in Figure 15.

The variable *year* indicated that after accounting for other variables, survival rates tended to be low in 2003 and especially 2004 in comparison to previous years (Table 13; Figure 15). The effect of *log(flow)* implied that survival rates declined rapidly as flows dropped below 3000 or 4000 cfs (Figure 15). Similar to spring Chinook, increases in both *migration day* and *travel time* were associated with declines in survival rates. Adding *temperature* to this model had little effect (P = 0.34). In sum, the full model accounted for 476.3 of the total deviance of 643.9 (Table 14), yielding an estimate of the dispersion parameter of $\hat{\phi}$ = 2.76. No obvious problems were evident among standard diagnostic plots of residuals.

Figure 16B shows observed survival rates and the predicted flow-survival relationship across years for the *log(flow)* model. This “average” relationship implies a strong influence of flow on survival rates. Under average conditions for other variables (*year*, *migration day* and *travel time*), the predicted survival rate is roughly 0.75 (75%) at 6000 cfs, 0.5 at 2000 cfs, and only about 0.2 at 500 cfs (Figure 16B). As discussed below, however, the strength of the flow-survival relationship depended critically on the form of the regression model.

Table 13. Regression coefficients and standard errors (SE) for the logistic model fit to 66 fall Chinook survival-rate estimates. Note that the coefficient for 1998 is taken to be zero, whereas the remaining *year* coefficients represent differences in logit(survival) relative to 1998.

Variable	Coefficient	SE
Intercept	2.71	2.99
Year = 1999	0.18	0.51
2000	0.12	0.94
2001	0.57	0.56
2003	-0.46	0.40
2004	-1.53	0.48
Log(Flow)	1.04	0.22
Migration day	-0.06	0.01
Travel time	-0.17	0.04

Table 14. Analysis of deviance for the logistic model fit to 66 fall Chinook survival-rate estimates. Df = degrees of freedom.

Variable	Df	Deviance	Residual df	Residual deviance	F Value	P-value
Intercept	1			643.9		
Year	5	206.5	60	437.4	14.9	P < 0.001
Log(Flow)	1	179.4	59	258.0	64.8	P < 0.001
Migration day	1	40.9	58	217.1	14.7	P < 0.001
Travel time	1	49.6	57	167.6	17.9	P < 0.001
Total	9	476.3	57	167.6		

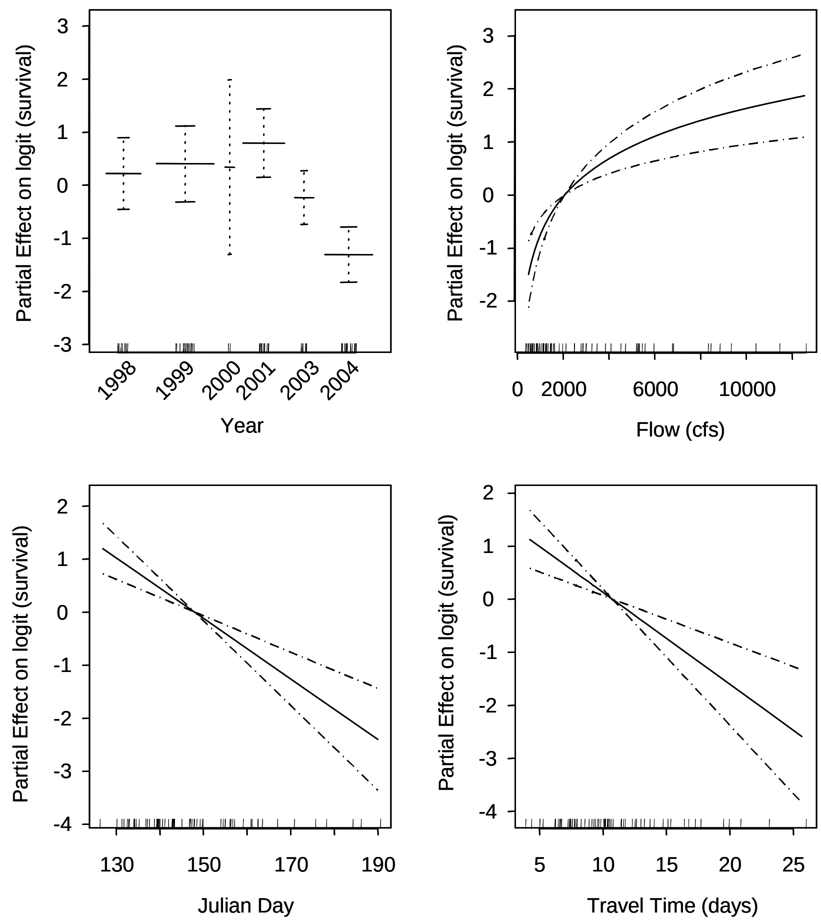


Figure 15. Partial effects of *year*, *log(flow)*, *migration day* and *travel time* on deviance residuals of logit(survival) for fall Chinook. Each plot has the same Y-axis scale so that the relative effect of each variable can be compared. Dashed lines indicate approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates for a given variable.

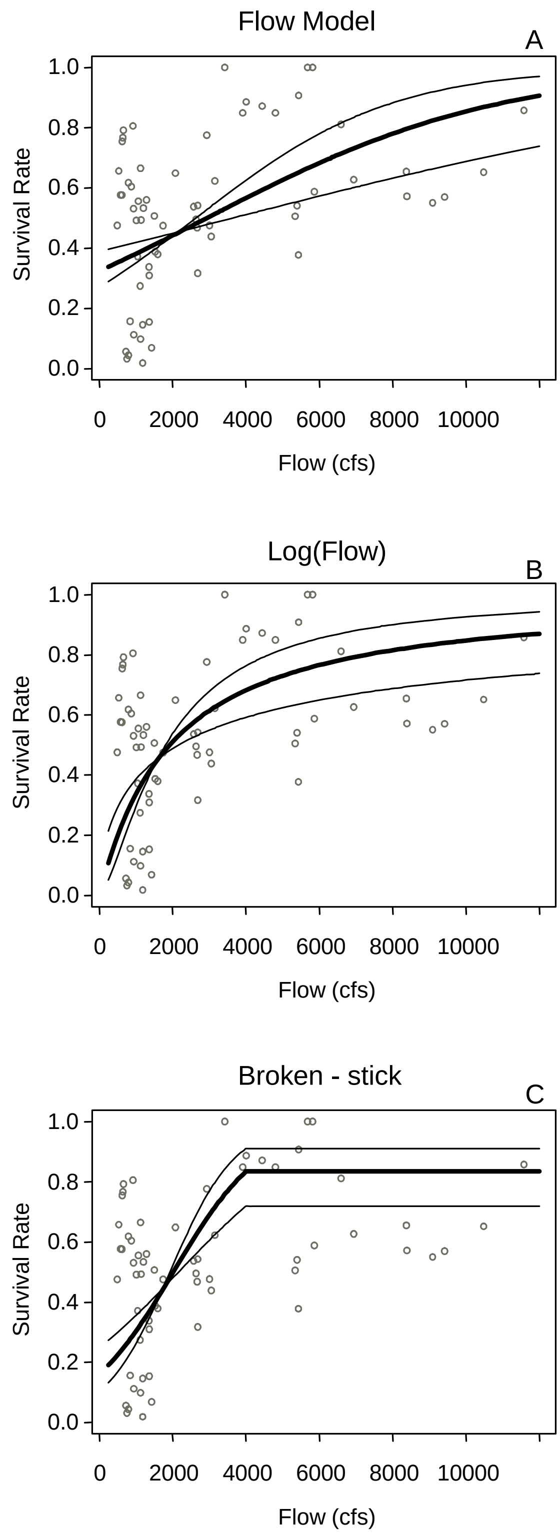


Figure 16. Predicted relationships (bold lines) between flow and fall Chinook survival rates across years for (A) the *flow* model, (B) the *log(flow)* model, and (C) the broken-stick model. Open circles are the observed survival rates. Thin lines are approximate 95% confidence intervals for the flow-survival relationship.

4.2.3. Alternative flow-survival relationships

Regressions using the *flow* form and especially the "broken-stick" form of the flow-survival relationship performed well based on AIC. In addition, estimated flow-survival relationships were found to be considerably weaker when the variable *year* was excluded from regressions. A summary of model results is provided in Table 15, where "Model 5" refers to the baseline *log(flow)* model discussed above.

Using *flow* instead of *log(flow)* in the baseline model produced an almost linear relationship that implied much more gradual effects of flow on survival than depicted for *log(flow)* (Figure 16A). The difference in AIC for *flow* compared to *log(flow)* was 5.1 (Table 15, Model 1), indicating that the statistical support for *flow* was considerably weaker than for *log(flow)*.

The fit of a GAM model suggested that there was strong evidence ($P < 0.001$) of non-linear relationship between *flow* and logit(survival) typical of the broken-stick form, with a plateau (breakpoint) at roughly 4000 cfs (Figure 17). We therefore fit a broken-stick model with a breakpoint at 4000 cfs. This model provided a better fit to the data than the *log(flow)* model, as indicated by a lower AIC value ($\Delta_i = -3.1$; Table 15, Model 9). The broken-stick model implied a strong effect of flow on survival up to 4000 cfs, though the relationship was not as steep as the *log(flow)* form for flows less than 1500 cfs (Figure 16).

Removing auxiliary variables (*travel time*, *day* and *year*) had little effect on predicted flow-survival relationships, except in the case of removing all three variables. Removing all variables substantially reduced flow coefficients and predicted flow-survival relationships for the *log(flow)* and broken-stick models (Table 15, Models 8 and 12) (Figure 18). The most influential variable was *year*, the last variable removed, although omitting *year* but including *day* did increase flow coefficients somewhat (results not shown). The importance of the *year* variable is not surprising because the two years with the lowest flows (2001 and 2004) had quite different survival-rate estimates. Survival rates were generally much higher in 2001 and lower in 2004 than depicted by the "average" flow-survival relationships (corresponding respectively to the preponderance of observations above and below the curves at low flows; Figure 16). This is reflected in the coefficients for *year* in the baseline *log(flow)* model, where 2001 has the highest *year* effect and 2004 the lowest (Table 13; Figure 15). Without such effects explicitly modeled in the regressions, the flow-survival relationships weaken. This was also evident among correlations between coefficients, which indicate the degree of dependence among different coefficients. For the *log(flow)* and broken-stick models, correlations between flow coefficients and those for the 2001 and 2004 years were roughly 0.6.

Table 15. **Flow coefficients and AIC values (Δi; differences from Model 5, the baseline model) for three alternative forms for the flow-survival relationship: the *flow*, *log(flow)*, and broken-stick forms. For each form, results are shown for the full model and models with each auxiliary variable removed one at a time. *K* is the number of parameters in a model. All AIC values were computed using the dispersion-parameter estimate for the baseline model ($\phi = 2.76$).**

Model	Form	Auxiliary variables	Flow Coefficient	Standard error	Residual Deviance	*K*	AIC (Δ_i)
1	Flow	Year+Day+Travel	0.00025	0.00006	181.6	9	5.1
2		Year+Day	0.00033	0.00007	241.8	8	24.9
3		Year	0.00035	0.00008	324.8	7	52.9
4		None (Flow only)	0.00023	0.00006	524.4	2	115.1
5	log(Flow)	Year+Day+Travel	1.04	0.22	167.6	9	0.0
6		Year+Day	1.31	0.23	217.1	8	15.9
7		Year	1.46	0.23	258.0	7	28.7
8		None (Flow only)	0.60	0.17	547.7	2	123.5
9	Broken-stick	Year+Day+Travel	0.00082	0.00015	153.6	10	-3.0
10		Year+Day	0.00102	0.00016	186.5	9	6.9
11		Year	0.00111	0.00015	210.4	8	13.5
12		None (Flow only)	0.00046	0.00011	509.0	3	111.5

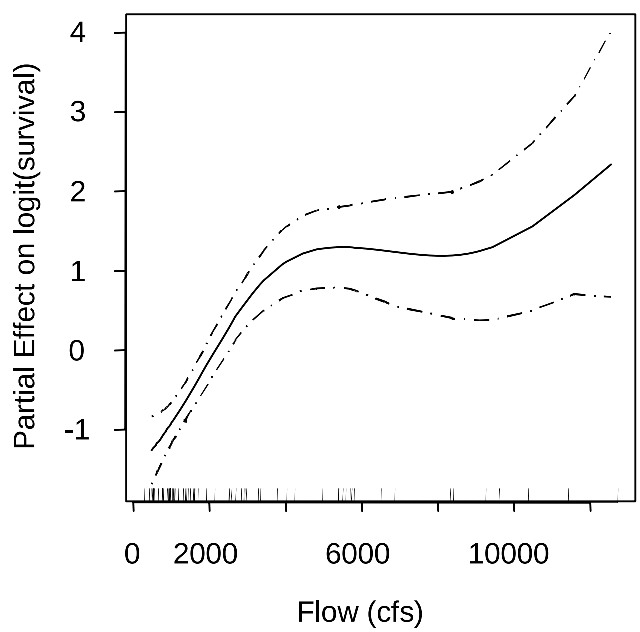


Figure 17. **Partial effect of flow on logit(survival) from estimated from a GAM model (i.e., the baseline model but with flow modeled using a smoothing spline). Dashed lines indicate approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates.**

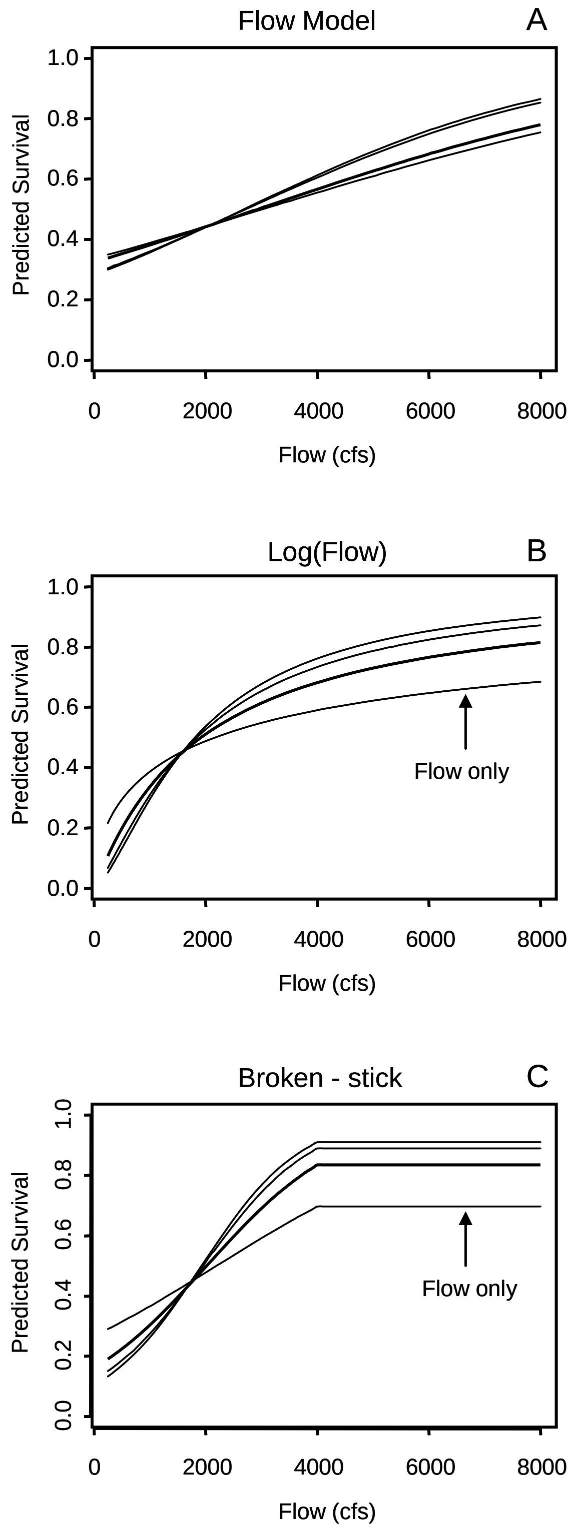


Figure 18. **Effect of removing auxiliary variables on the predicted flow-survival relationships for** (A) **the** ***flow*** **model (Table 15, Models 1-4),** (B) **the** ***log(flow)*** **model (Models 5-8), and** (C) **the broken-stick model (Models 9-12). Bold lines are the full models (Models 1, 4, and 9). Thin lines represent models with variables removed; in most cases these are similar to the full models with notable exceptions being** ***log(flow)*** **and broken-stick models with all variables removed (denoted "Flow only").**

4.2.4. *Effects of flow increases on smolt abundance*

Potential benefits of flow increases on fall Chinook smolt abundance were estimated using coefficients for the *flow*, *log(flow)*, and Broken-stick models (Table 15, Models 1, 5, and 9). Note that based on AIC, the Broken-stick model was the best-ranked model followed by *log(flow)*.

Estimates of the percent increase in the number of smolts surviving to McNary are shown for each flow scenario in Table 16 and Figure 19. Estimates for the *flow* model were generally low (less than 15%) across scenarios and years. In contrast, estimates of increases in smolt abundance for the *log(flow)* model ranged from roughly 14% to 31% for the average year (2003), and from 46% to 96% for the dry year (2001), depending on the scenario. In comparison, estimates for the Broken-stick model were similar for the average year (11% to 28%) but somewhat lower for the dry year (16% to 42%).

Table 16. Estimates of the percent increase in the number of fall Chinook smolts surviving to McNary as a result of anticipated flow increases for each alternative flow scenario. Ranges in brackets are approximate 95% prediction intervals based on intervals for flow coefficients.

Flow	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	2.4 (1.5 - 2.7)	5.0 (2.6 - 7.0)	5.2 (2.5 - 8.0)
3a	3.3 (2.1 - 3.8)	6.9 (3.6 - 9.8)	7.3 (3.6 - 11.4)
3b	4.1 (2.6 - 4.8)	8.9 (4.6 - 12.5)	9.5 (4.6 - 14.8)
3c	3.5 (2.2 - 4.1)	7.5 (3.9 - 10.6)	8.0 (3.9 – 12.3)
3d	4.4 (2.8 - 5.1)	9.4 (4.9 - 13.3)	10.2 (4.9 - 15.8)
4a	5.3 (3.4 - 6.1)	11.5 (6.0 - 16.2)	12.4 (6.0 - 19.4)
4b	5.6 (3.5 - 6.4)	12.1 (6.3 - 17.0)	13.1 (6.3 - 20.4)

Log(flow)	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	1.9 (1.2 - 2.4)	10.2 (6.5 - 12.8)	46.4 (24.6 - 72.9)
3a	2.6 (1.7 - 3.3)	13.9 (8.8 - 17.7)	62.3 (32.6 - 99.4)
3b	3.3 (2.1 - 4.2)	17.3 (10.9 - 22.3)	76.5 (39.7 - 123.2)
3c	2.8 (1.8 - 3.6)	14.9 (9.4 - 19.1)	66.4 (34.7 - 106.3)
3d	3.5 (2.2 - 4.4)	18.3 (11.5 - 23.6)	80.2 (41.5 - 129.5)
4a	4.2 (2.7 - 5.3)	21.8 (13.6 - 28.3)	93.2 (47.9 - 151.2)
4b	4.4 (2.8 - 5.5)	22.8 (14.1 - 29.6)	96.5 (49.5 - 156.8)

Broken-stick	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	2.1 (1.3 - 2.8)	11.4 (7.7 - 14.1)	16.2 (10.2 - 22.6)
3a	2.8 (1.8 - 3.8)	16.0 (10.9 - 20)	23.2 (14.5 - 32.5)
3b	3.5 (2.2 - 4.7)	20.6 (13.9 - 25.8)	30.3 (18.9 - 42.5)
3c	3.0 (1.9 - 4.1)	17.4 (11.8 - 21.7)	25.2 (15.8 - 35.3)
3d	3.7 (2.3 - 5.0)	22.0 (14.8 - 27.5)	32.3 (20.1 - 45.3)
4a	4.3 (2.6 - 5.8)	26.9 (18.1 - 33.8)	39.8 (24.8 - 55.7)
4b	4.4 (2.7 - 6.0)	28.3 (19 - 35.5)	41.8 (26.0 - 58.6)

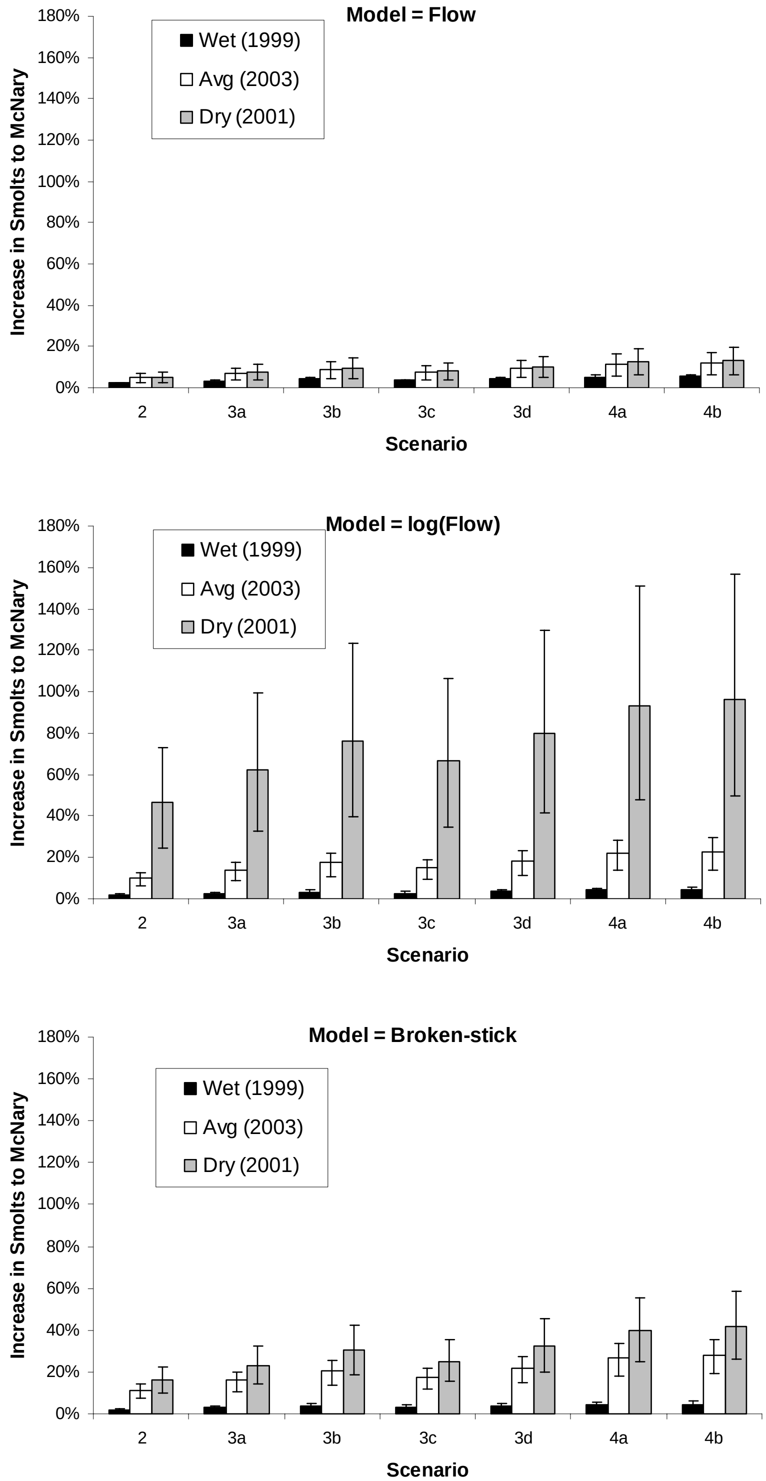


Figure 19. Estimates of the percent increase in the number of fall Chinook smolts surviving to McNary as a result of anticipated flow increases for each flow scenario. Error bars indicate approximate 95% prediction intervals based on confidence intervals for flow coefficients.

4.2.5. Effects of flow increases on adult returns

Estimated increases in adult abundance for fall Chinook based on “model averaging” are shown in Table 17, while estimates for each form of the flow-survival relationship are shown in Table 18. The AIC weights (w_i) used in model averaging were 0.01, 0.18, and 0.81 for the *flow*, *log(flow)*, and broken-stick forms, respectively. Thus, abundance estimates were heavily weighted toward the broken-stick model, which had the strongest support based on AIC.

For model averaging, estimates of proportional increases in adult abundance ranged from roughly 10% to 23% for the “historic” frequency of future year types (“25/25/50” or 25% wet, 25% dry, and 50% average years), and from 16% to 39% for the pessimistic assumption (“50/50” or 50% dry and 50% average years) (Table 17). Numeric increases ranged 181 to 615 adults when based on an expected return equal to the recent 15-year geometric mean, and from roughly 328 to 1112 adults given the EDT Restoration abundance, depending on the scenario (Table 17). Adult estimates were roughly 50% greater under the pessimistic assumption for future year types because of the relatively strong flow-survival relationship estimated for fall Chinook.

Estimates specific to each flow-survival relationship depict considerable uncertainty in adult estimates (Table 18). In general, estimates for the preferred broken-stick model were 2 to 3 times greater than for the *flow* model, but about 25% lower than for the *log(flow)* model. For broken-stick estimates, approximate 95% confidence intervals ranged from roughly 65% to 135% of a given estimate. Note, however, that confidence intervals in Table 18 should be interpreted with extreme caution because (1) they are based only on uncertainty in the flow-survival relationship for a given model, and (2) they do not account for uncertainty in other critical assumptions, in particular the assumption changes in adult abundance will be directly proportional to changes in smolt abundance at McNary.

Table 17. Estimates of average annual increases in fall Chinook adult abundance based on “model averaging.” Results are shown for each flow scenario and two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). N = expected annual abundance (geometric mean) given unadjusted flow conditions.

	Percent (%) increase		Numeric increase based on 15-yr mean		Numeric increase based on EDT Restoration	
Scenario	25/25/50	50/50	25/25/50 (N = 1,883)	50/50 (N = 1,579)	25/25/50 (N = 3,406)	50/50 (N = 2,856)
2	9.6	16.0	181	252	328	456
3a	13.5	22.4	254	354	460	641
3b	17.3	28.7	325	454	588	821
3c	14.6	24.3	275	383	497	693
3d	18.3	30.6	345	482	624	873
4a	22.2	37.1	418	586	757	1061
4b	23.3	38.9	438	615	793	1112

Table 18. Estimates of average annual increases in fall Chinook adult abundance for each flow scenario and flow-survival relationship (*flow*, *log(flow)*, and broken-stick forms). Results are shown for two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). Ranges in brackets are approximate 95% prediction intervals based on smolt estimates. N = expected annual abundance (geometric mean) given unadjusted flow conditions.

Flow	Percent (%) increase		Numeric increase based on 15-yr mean (N = 1,883)		Numeric increase based on EDT Restoration (N = 3,406)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 1,505)	25/25/50	50/50 (N = 2,722)
2	4.0 (2.2 - 5.5)	5.0 (2.6 - 7.1)	76 (41 - 103)	76 (40 - 107)	137 (74 - 186)	137 (72 - 194)
3a	5.6 (3.1 - 7.7)	7.1 (3.7 - 10.1)	106 (58 - 145)	107 (56 - 152)	192 (104 - 262)	194 (102 - 274)
3b	7.2 (3.9 - 9.8)	9.2 (4.8 – 13.0)	136 (74 - 185)	138 (72 - 195)	245 (133 - 335)	249 (130 - 353)
3c	6.1 (3.3 - 8.3)	7.7 (4.0 - 10.9)	115 (62 - 157)	116 (61 - 164)	208 (113 - 283)	210 (110 - 297)
3d	7.7 (4.2 - 10.5)	9.7 (5.1 - 13.8)	144 (78 - 197)	147 (77 - 208)	261 (141 - 357)	265 (138 - 376)
4a	9.3 (5.1 - 12.8)	11.9 (6.2 – 16.9)	176 (95 - 241)	179 (93 - 255)	318 (172 - 435)	324 (169 - 461)
4b	9.8 (5.3 - 13.4)	12.5 (6.5 – 17.8)	185 (100 - 253)	188 (98 - 268)	334 (181 - 457)	341 (177 - 485)

Log(Flow)	Percent (%) increase		Numeric increase based on 15-yr mean (N = 1,883)		Numeric increase based on EDT Restoration (N = 3,406)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 1,444)	25/25/50	50/50 (N = 2,613)
2	12.5 (7.7 - 16.5)	23.6 (14.3 - 31.5)	236 (145 - 312)	341 (207 - 455)	426 (261 - 564)	617 (374 - 823)
3a	16.9 (10.3 - 22.7)	31.8 (19.1 - 43.1)	319 (193 - 427)	460 (276 - 623)	577 (350 - 772)	832 (499 - 1126)
3b	20.9 (12.6 - 28.3)	39.2 (23.3 - 53.6)	394 (237 - 532)	567 (336 - 774)	713 (429 - 963)	1025 (608 - 1400)
3c	18.1 (11.0 - 24.3)	34.0 (20.3 - 46.2)	341 (206 - 458)	491 (294 - 667)	617 (373 - 829)	889 (531 - 1207)
3d	22.0 (13.2 - 29.8)	41.2 (24.4 - 56.5)	415 (249 - 561)	596 (353 - 815)	751 (451 - 1016)	1077 (638 - 1475)
4a	25.9 (15.5 - 35.2)	48.2 (28.4 - 66.4)	488 (291 - 663)	697 (410 - 959)	883 (526 - 1200)	1260 (741 - 1734)
4b	26.9 (16.0 - 36.7)	50.0 (29.4 - 69.0)	507 (302 - 690)	723 (425 - 996)	917 (546 - 1249)	1307 (768 - 1802)

Broken-stick	Percent (%) increase		Numeric increase based on 15-yr mean (N = 1,883)		Numeric increase based on EDT Restoration (N = 3,406)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 1,610)	25/25/50	50/50 (N = 2,912)
2	9.1 (6.0 - 11.7)	14.6 (9.6 – 19.1)	171 (114 - 221)	236 (154 - 308)	310 (205 - 400)	426 (279 - 556)
3a	12.9 (8.5 - 16.7)	20.8 (13.6 - 27.3)	243 (160 - 314)	335 (219 - 440)	439 (289 - 568)	607 (395 - 795)
3b	16.6 (10.9 - 21.6)	27.0 (17.5 - 35.5)	313 (205 - 406)	435 (282 - 571)	566 (371 - 735)	786 (511 - 1034)
3c	14.0 (9.2 - 18.1)	22.6 (14.7 - 29.7)	263 (173 - 341)	364 (237 - 477)	476 (313 - 617)	658 (429 - 864)
3d	17.7 (11.6 – 23.0)	28.8 (18.7 - 37.9)	333 (218 - 433)	463 (301 - 609)	603 (395 - 783)	838 (544 - 1102)
4a	21.6 (14.1 - 28.2)	35.4 (22.9 - 46.6)	407 (266 - 530)	569 (368 - 750)	737 (482 - 959)	1030 (666 - 1356)
4b	22.7 (14.8 - 29.6)	37.2 (24.0- 49.0)	428 (279 - 557)	599 (387 - 788)	774 (505 - 1008)	1083 (700 - 1426)

4.3. Coho Salmon

4.3.1. Data summary

There were two primary *release types* for coho salmon: hatchery fish released well above Prosser and “unidentified” fish released at or near Prosser. An initial regression model found only a weak difference (P = 0.19) between these groups. We therefore focus on analyses in which data were pooled across all releases to estimate survival rates. A total of 126 observations were available across years based on minimum release-group size of 25 or more fish (Table 19).

Table 19. Number of daily survival-rate estimates for coho smolts for release groups of 25 or more fish.

Year	Estimates
1998	22
1999	19
2000	20
2001	22
2002	13
2003	20
2004	10
Total	126

Survival-rate estimates for coho smolts were high in 1998 and 1999 (Figure 20); in fact, many estimates in these years were greater than one and were therefore constrained to one. In both years, migrating smolts experienced high flows and low temperatures (Figure 20). Survival rates were lowest in years with low flows (2001 and 2004). High temperatures were also experienced in 2001. Travel times for coho smolts were consistently lower across years than for spring and fall Chinook (Figure 20).

There was little consistency across years in either trends between variables and migration day (Figure 21), or trends between survival-rates estimates and each variable (Figure 22). The most obvious patterns were the general differences among years in medians and ranges of survival-rate estimates, migration day, flows, and temperatures (Figure 20).

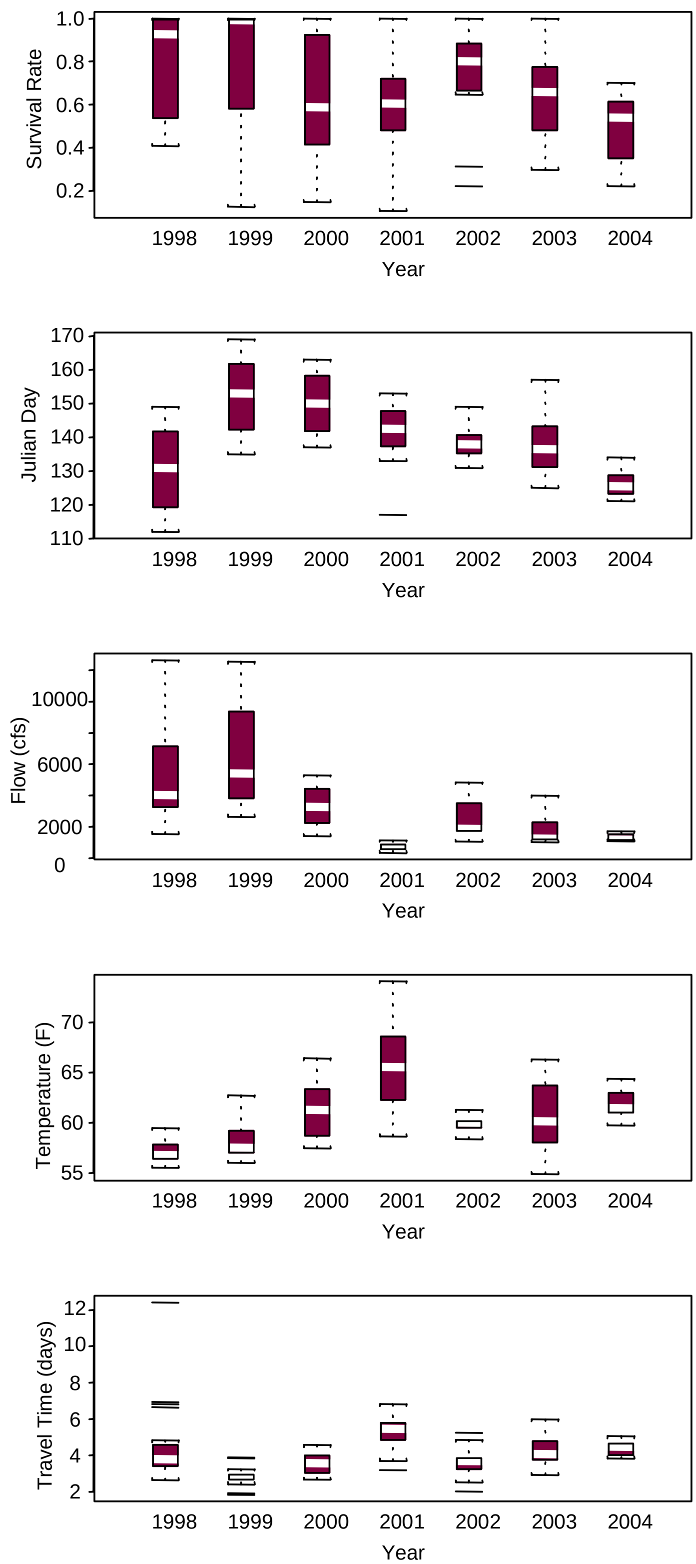


Figure 20. Box-plots of coho survival-rate estimates, migration day, flow, temperature, and median travel time for each year.

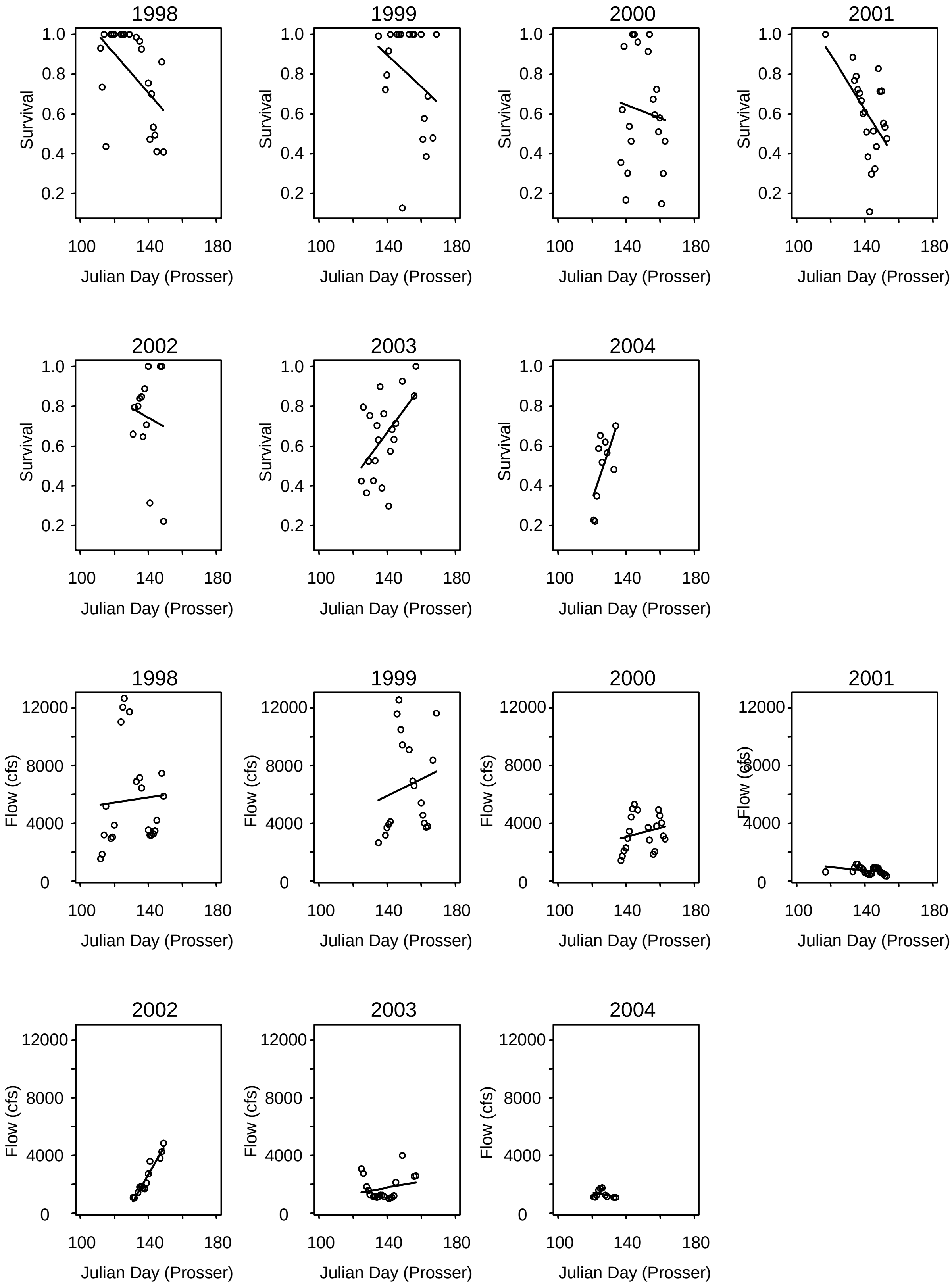
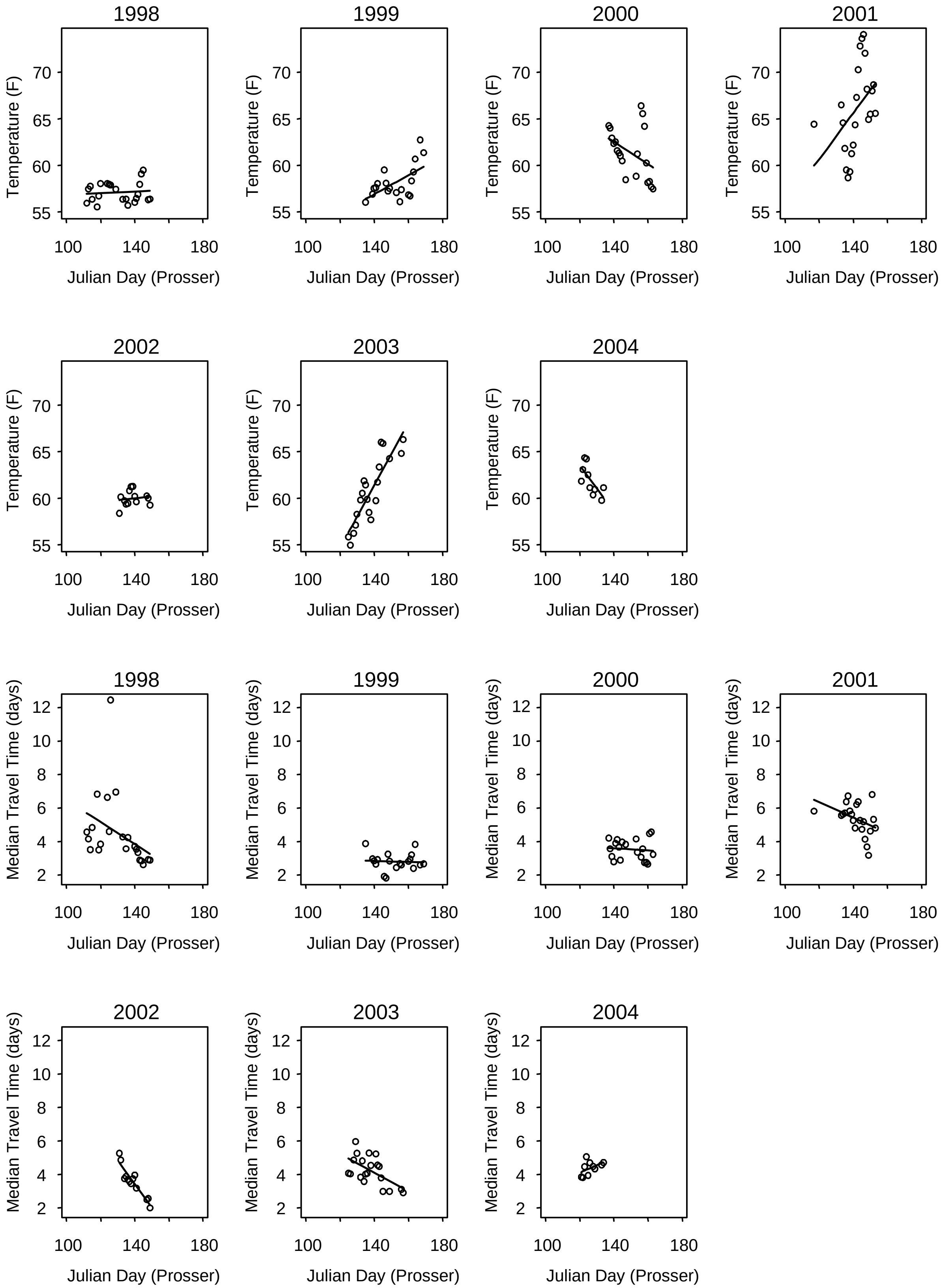


Figure 21. Coho survival-rate estimates, flows, temperatures, and median travel times as a function of migration day for each year.



1998
1999
2000
2001
2002
2003
2004
Temperature (F)
Median Travel Time (days)
Julian Day (Prosser)

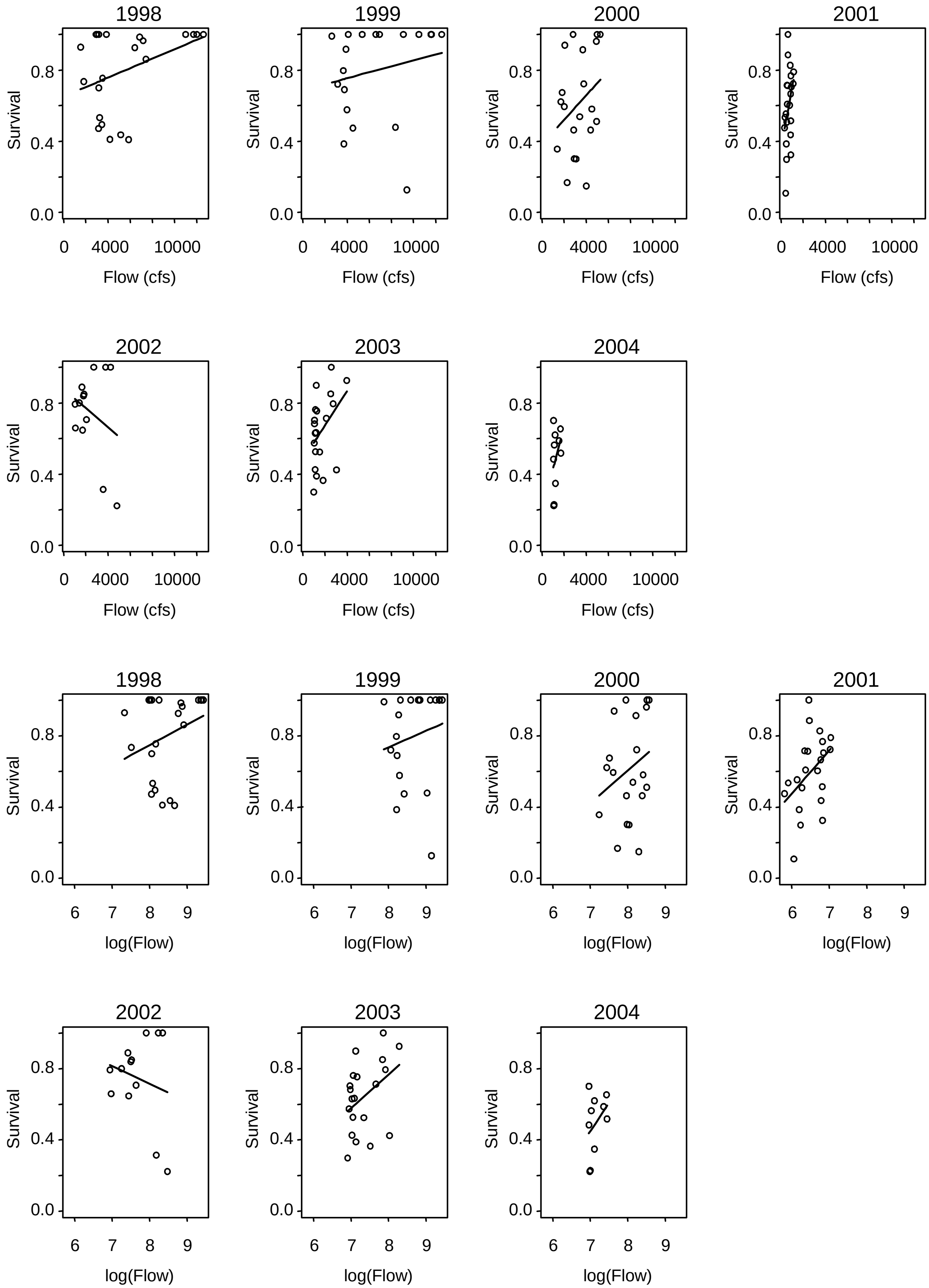


Figure 22. Coho survival-rate estimates as a function of flow, log(flow), temperature and median travel time for each year.

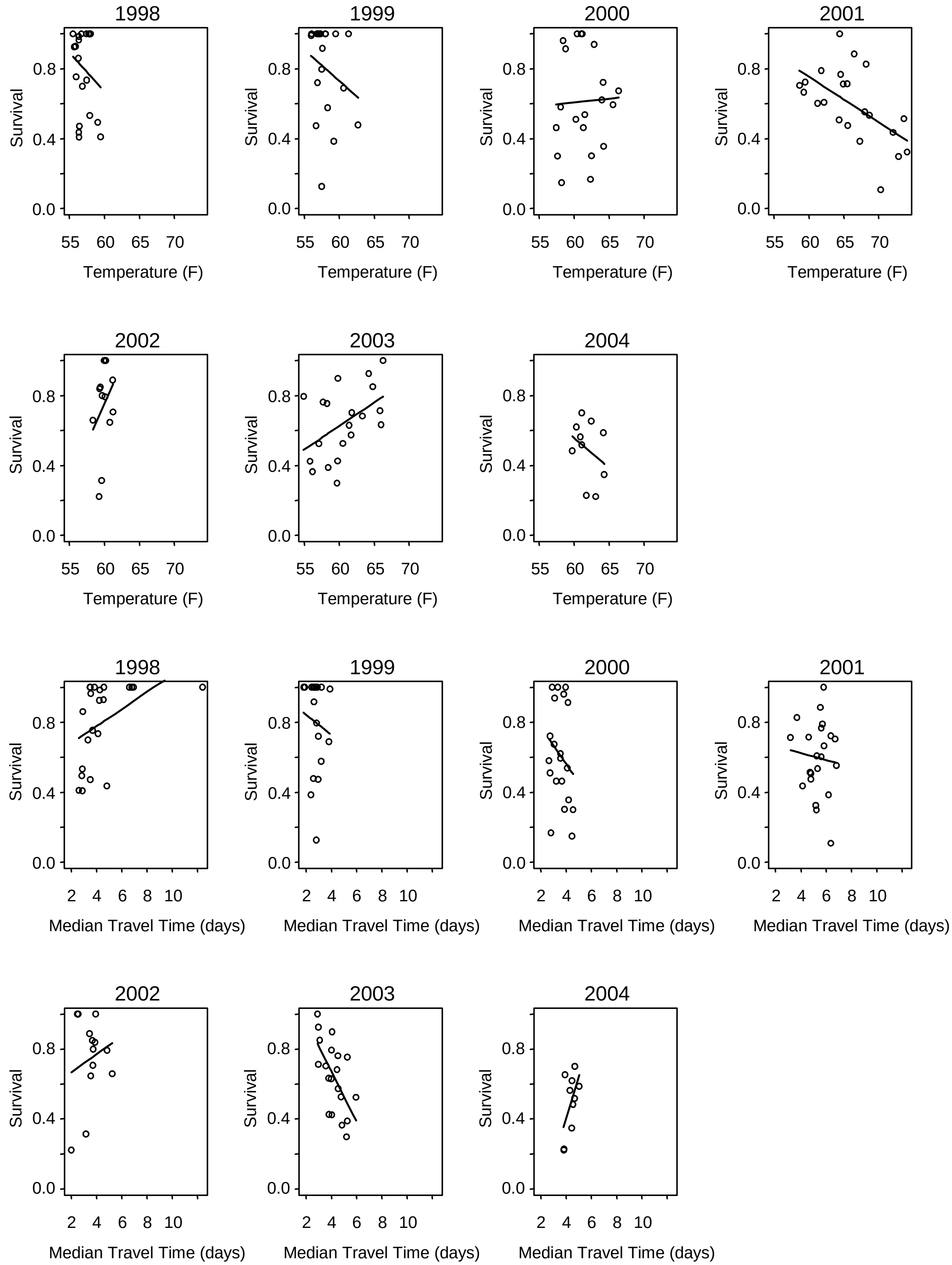


Figure 22. Continued.

4.3.2. Baseline logistic regression model

Initially, the "best" logistic model for coho salmon included the variables *temperature*, *flow*, *year*, *day* and *travel time*. The dominant explanatory variable was *temperature*, which had a negative association with survival (i.e., low survival at high temperature). However, the fit of a GAM model strongly suggested that the relationship between temperature and logit(survival) was nonlinear, with temperature having a pronounced negative effect above roughly 67 degrees F (Figure 23). We therefore modeled *temperature* as a "broken-stick" and found that this form was a significant improvement over the original linear form (e.g., AIC was reduced by 11.8 despite the addition of one parameter). Consequently, the baseline model and all subsequent models examined contained this broken-stick form for *temperature*.

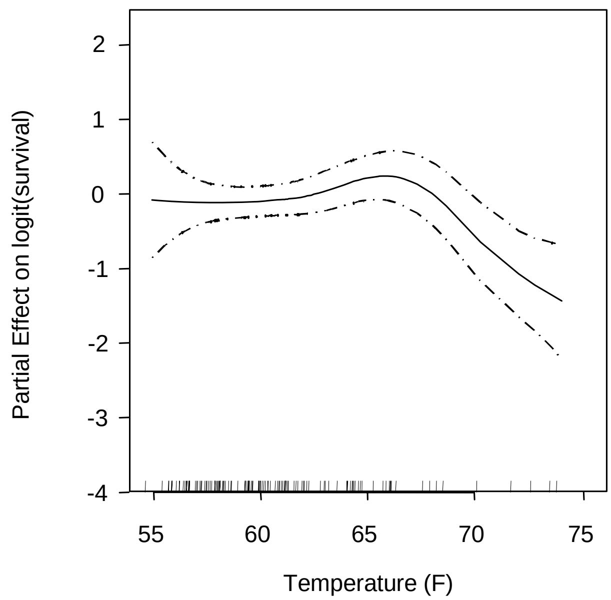


Figure 23. Partial effect of temperature on logit(survival) estimated from a GAM model. Dashed lines are approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates.

Summaries of regression coefficients and analysis of deviance for the baseline model are provided in Table 20 and Table 21. Plots of the partial effects of each variable on logit(survival) are shown in Figure 24.

In the baseline model, the linear form *flow* showed a positive effect of flow on survival (Table 20; Figure 24). The variable *year* indicated that after accounting for other variables, survival tended to be high in 2001 and low in 2004 compared to other years. Once again, both *migration day* and *travel time* had apparent negative effects on survival rates. Note that *migration day* and *travel time* were not important variables unless *year* was included in the regression. In sum, the full model accounted for 425.1 of the total deviance of 955.3 (Table 21). The estimate of the dispersion parameter was $\hat{\phi}$ = 4.95. No obvious problems were evident among standard diagnostic plots of residuals.

Figure 25A shows observed survival rates and the predicted flow-survival relationship across years for the baseline *flow* model. This "average" relationship is nearly linear and implies a relatively minor effect of flow on survival rates.

Table 20. Regression coefficients and standard errors (SE) for the logistic model fit to 126 coho survival-rate estimates. Note that the coefficient for 1998 is taken to be zero, whereas the remaining *year* coefficients represent differences in logit(survival) relative to 1998.

Variable	Coefficient	SE
Intercept	6.03	1.71
Temperature	-0.24	0.05
Flow	0.00029	0.00009
Year = 1999	0.54	0.52
2000	0.18	0.43
2001	1.36	0.50
2002	0.80	0.51
2003	0.54	0.46
2004	-0.64	0.51
Migration Day	-0.04	0.01
Travel time	-0.28	0.09

Table 21. Analysis of deviance for the logistic model fit to 126 coho survival-rate estimates. Df = degrees of freedom.

Variable	Df	Deviance	Residual df	Residual deviance	F Value	P-value
Intercept	1		125	955.3		
Temperature	1	203.7	124	751.6	41.2	P < 0.001
Flow	1	79.7	123	671.9	16.1	P < 0.001
Year	6	69.6	117	602.3	2.3	P = 0.036
Migration day	1	29.5	116	572.8	6.0	P = 0.016
Travel time	1	42.6	115	530.2	8.6	P = 0.004
Total	11	425.1	115	530.2		

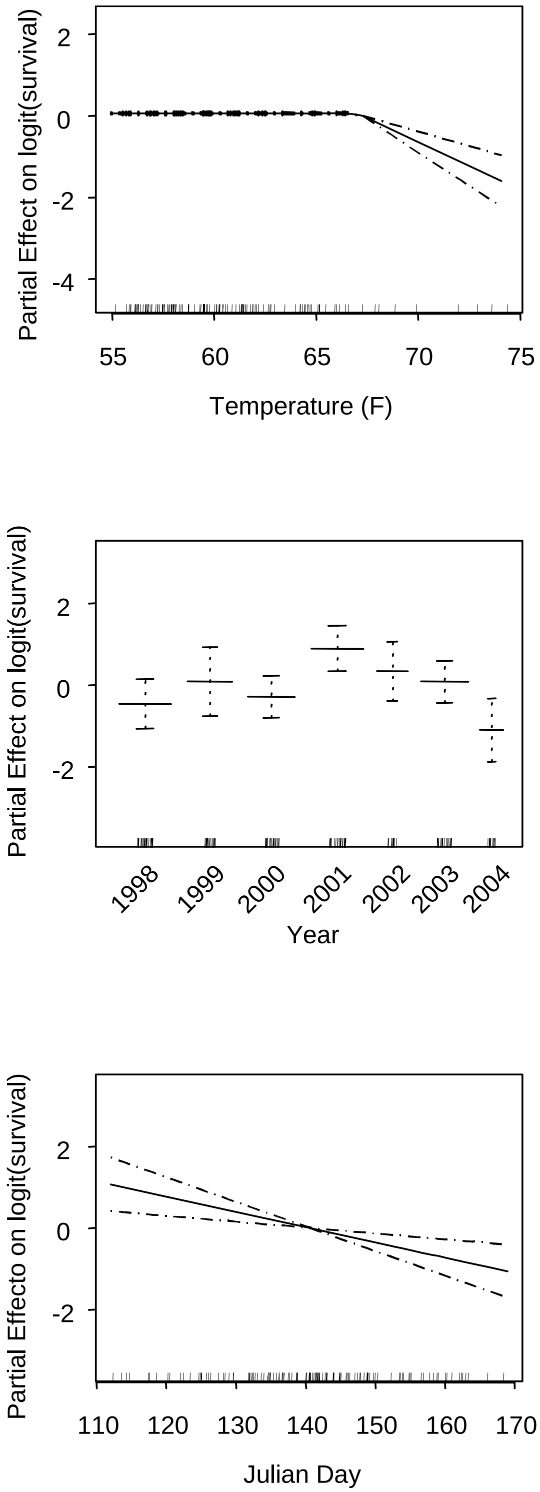


Figure 24. Partial effects of *temperature* (broken-stick), *flow*, *year*, *migration day*, and *travel time* on deviance residuals of logit(survival) for coho smolts. Each plot has the same Y-axis scale so the relative effect of each variable can be compared. Dashed lines indicate approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates for a given variable.

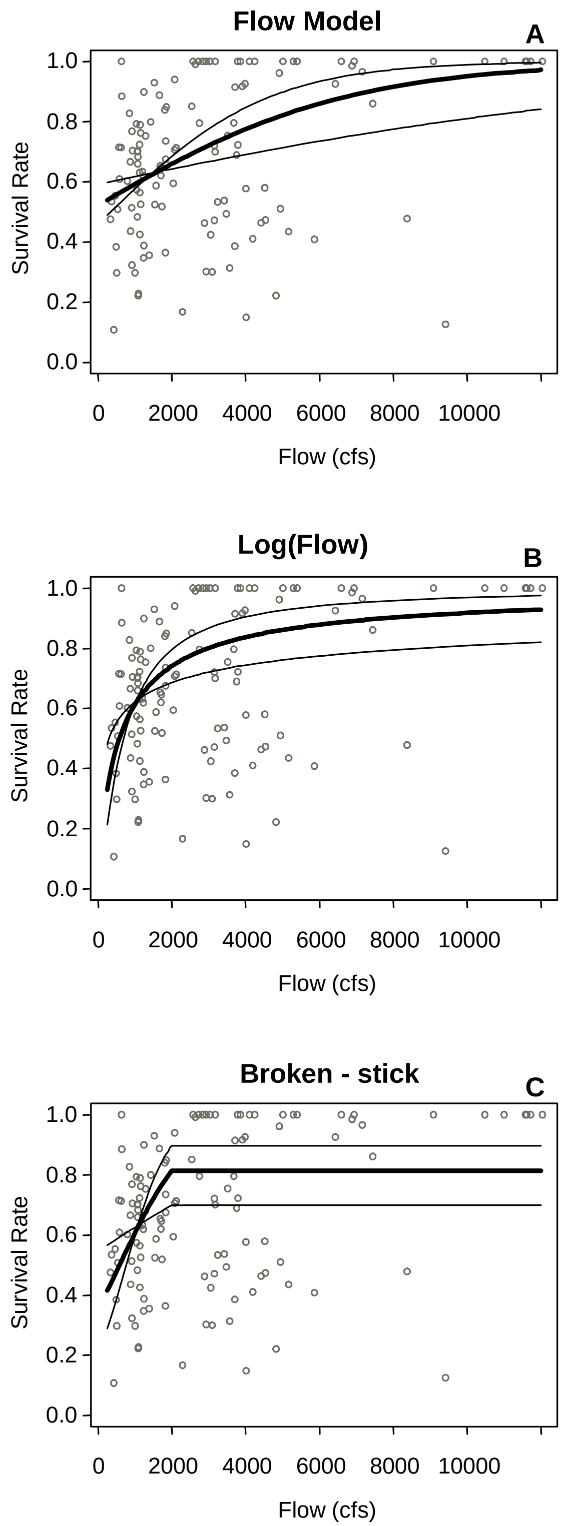


Figure 25. Predicted relationships (bold lines) between flow and coho survival rates across years for (A) the *flow* model, (B) the *log(flow)* model, and (C) the broken-stick model. Open circles are the observed survival rates. Thin lines are approximate 95% confidence intervals for the flow-survival relationship.

4.3.3. Alternative flow-survival relationships

Regressions using *log(flow)* performed better than the baseline *flow* form, while "broken-stick" forms performed worse. Similar to fall Chinook, estimated flow-survival relationships were considerably weaker when the variable *year* was excluded from regressions. A summary of model results is provided in Table 22, where "Model 1" refers to the baseline *flow* model discussed above.

Using *log(flow)* instead of *flow* in the baseline model reduced the AIC value (Δ_i = -1.3; Table 22, Model 6) and implied much greater effects of flow on survival rates at low flows (Figure 25). The reduction in AIC indicates that the *log(flow)* form provided a slightly improved fit to the data. (Note that this was not revealed in the initial selection of the baseline model, which contained the linear form *flow* prior to modifying the form for *temperature* to a broken-stick model.)

The fit of a GAM model confirmed that there was only weak evidence ($P < 0.10$) of a nonlinear relationship between *flow* and logit(survival) (Figure 26). Because the relationship between *flow* and logit(survival) appeared to plateau somewhat at roughly 2000 cfs (Figure 26), we also examined a broken-stick model with a breakpoint at 2000 cfs. The AIC for this model indicated that it had relatively weak support in comparison to the baseline model (Δ_i = 6.9; Table 22, Model 11) or the *log(flow)* model (Δ = 8.2; Model 11 versus Model 6). The broken-stick model implied a reasonably strong effect of low flows on survival, similar to the *log(flow)* form (Figure 25).

Removing variables *travel time* and *day* had little effect on predicted flow-survival relationships (Table 22; Figure 27); however, removing *year* reduced flow coefficients dramatically, especially for the *log(flow)* and broken-stick models (Table 22, Models 9 and 14). The effects of removing *year* on flow-survival relationships are illustrated in Figure 27 for curves labeled "Temperature" (i.e., the only remaining variable). Removing all variables including *temperature* also resulted in reduced flow coefficients (Table 22; Figure 27).

Similar to fall Chinook, the importance of *year* arises because survival-rate estimates were quite variable across years with low flows (2001, 2003 and 2004) (e.g., Figure 20). In particular, estimates in 2001 were moderate despite very low flows, and consequently, the strong flow-survival relationship depicted by the full *log(flow)* model (Figure 25) was associated with a high *year* coefficient for 2001 (1.62 compared to 1.36 for the *flow* model). Correlations between the *log(flow)* coefficient and the 2001, 2003, and 2004 *year* coefficients were 0.73, 0.50, and 0.51, respectively, indicating a strong dependence among these estimates.

Table 22. Flow coefficients and AIC values (Δi; differences from Model 1, the baseline model) for the *flow*, *log(flow)*, and broken-stick forms of the flow-survival relationship. For each form, results are shown for the full model and models with each auxiliary variable removed one at a time. *K* is the number of parameters in a model (one parameter was added to all model to account for the broken-stick form for *temperature*). All AIC values were computed using the dispersion-parameter estimate for the baseline model (ϕ = 4.95).

Model	Form	Auxiliary variables	Flow Coefficient	Standard error	Residual Deviance	*K*	AIC (Δ_i)
1	Flow	Temp+Year+Day+Travel	0.00029	0.00009	530.2	11	0.0
2		Temp+Year+Day	0.00028	0.00010	572.8	10	6.6
3		Temp+Year	0.00025	0.00009	602.3	9	10.6
4		Temperature	0.00017	0.00005	671.9	3	12.6
5		None (Flow only)	0.00024	0.00006	801.5	2	36.8
6	log(Flow)	Temp+Year+Day+Travel	0.84	0.22	523.9	11	-1.3
7		Temp+Year+Day	0.91	0.22	545.3	10	1.1
8		Temp+Year	0.94	0.22	560.8	9	2.2
9		Temperature	0.38	0.10	681.7	3	14.6
10		None (Flow only)	0.53	0.11	796.5	2	35.8
11	Broken-stick	Temp+Year+Day+Travel	0.00104	0.00035	554.3	12	6.9
12		Temp+Year+Day	0.00118	0.00035	572.8	11	8.6
13		Temp+Year	0.00127	0.00035	586.7	10	9.4
14		Temperature	0.00040	0.00014	711.7	4	22.7
15		None (Flow only)	0.00064	0.00014	833.7	3	45.3

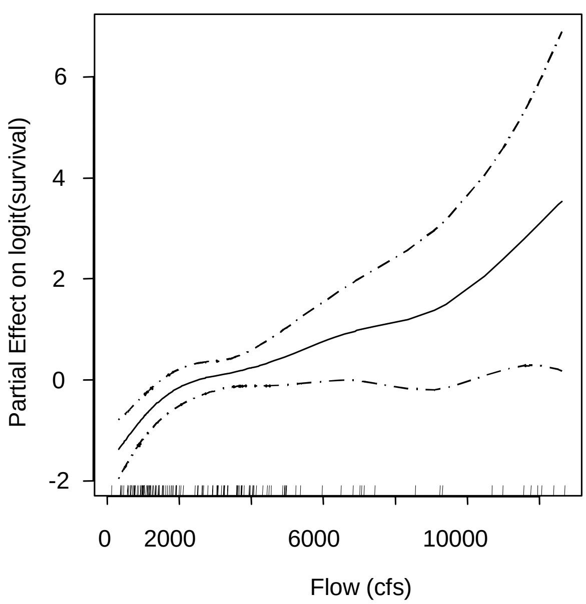


Figure 26. Partial effect of flow on logit(survival) estimated from a GAM model (i.e., the baseline model but with flow modeled using a smoothing spline). Dashed lines indicate approximate 95% pointwise confidence intervals. Tick marks on the X-axis show locations of survival-rate estimates.

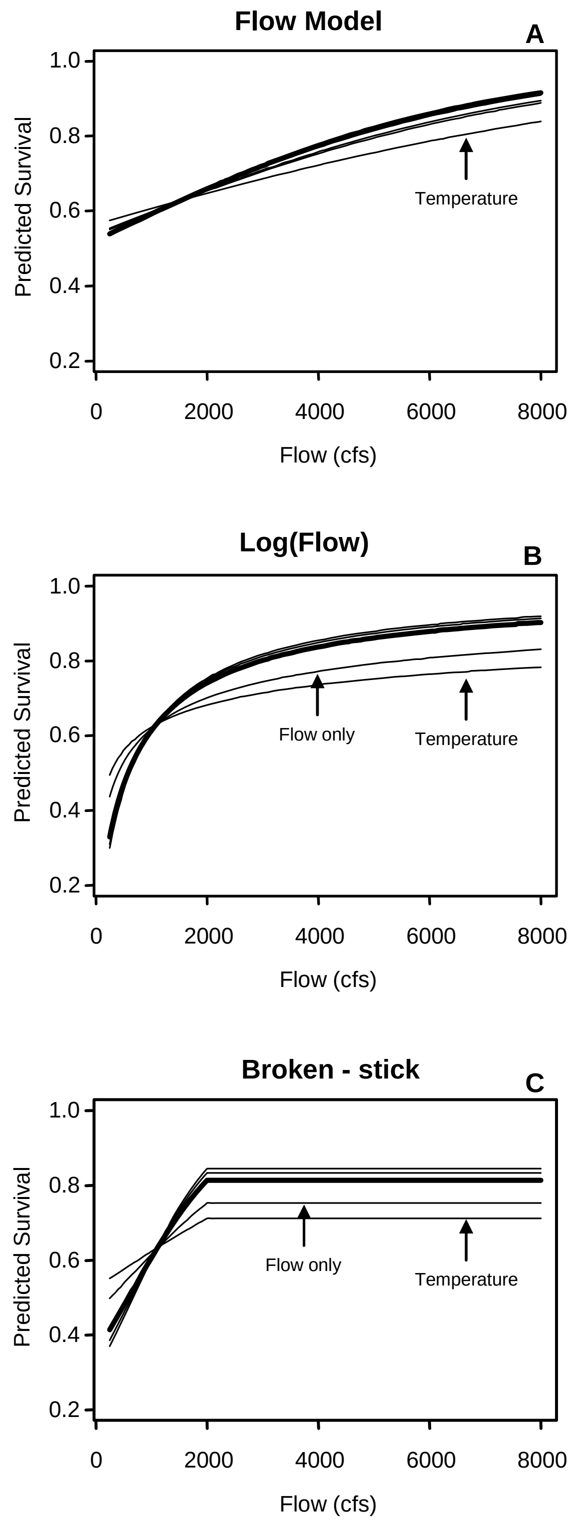


Figure 27. **Effect of removing auxiliary variables on the predicted flow-survival relationships for** (A) **the *flow* model (Table 22, Models 1-5),** (B) **the *log(flow)* model (Models 6-10), and** (C) **the broken-stick model (Models 11-15). Bold lines are the full models (Models 1, 6, and 11). Thin lines represent models with variables removed; these are similar to the full models with the exception of models with only *temperature* or with all variables removed (denoted "Flow only")**

4.3.4. Effects of flow increases on smolt abundance

Potential benefits of flow increases on coho smolt abundance were estimated using coefficients for the *flow*, *log(flow)*, and broken-stick models (Table 22, Models 1, 6, and 11). Note that based on AIC, the *flow* and *log(flow)* models both performed well, while support for the broken-stick model was considerably weaker.

Estimates of the percent (%) increase in the number of smolts surviving to McNary are shown for each of the seven scenarios in Table 23 and Figure 28. Estimates for the *flow* model were generally low (less than 8%) across scenarios and years. In contrast, estimates for both the *log(flow)* and broken-stick models ranged from roughly 5% to 11% for the average year (2003), and from 11% to 27% for the dry year (2001), depending on the scenario.

Table 23. Estimates of the percent (%) increase in the number of coho smolts surviving to McNary as a result of anticipated flow increases for each alternative flow scenario. Ranges in brackets are approximate 95% prediction intervals based on intervals for flow coefficients.

Flow	Wet (1999)	Avg (2003)	Dry (2001)
Scenario 2	1.2 (0.5 - 1.8)	3.2 (1.3 - 4.8)	3.1 (1.2 - 5.1)
3a	1.7 (0.7 - 2.5)	4.5 (1.8 - 6.5)	4.4 (1.6 - 7.1)
3b	2.1 (0.9 - 3.1)	5.6 (2.3 - 8.2)	5.6 (2.1 - 9.1)
3c	1.8 (0.8 - 2.7)	4.8 (2.0 - 7.1)	4.7 (1.8 - 7.7)
3d	2.3 (1.0 - 3.3)	6.0 (2.5 - 8.7)	6.0 (2.3 - 9.7)
4a	2.7 (1.2 - 3.9)	7.2 (3 - 10.4)	7.2 (2.7 - 11.7)
4b	2.8 (1.2 - 4.1)	7.5 (3.2 - 10.9)	7.6 (2.9 - 12.2)
Log(flow)	1999	2003	2001
Scenario 2	0.8 (0.4 - 1.3)	4.9 (2.6 - 6.8)	14.6 (6.9 - 22.4)
3a	1.2 (0.5 - 1.8)	6.5 (3.5 - 9.0)	18.8 (9.0 - 28.8)
3b	1.4 (0.7 - 2.2)	7.9 (4.2 - 10.8)	22.4 (10.8 - 34.0)
3c	1.2 (0.6 - 1.9)	6.9 (3.7 - 9.5)	19.9 (9.5 - 30.3)
3d	1.5 (0.7 - 2.3)	8.3 (4.5 - 11.3)	23.3 (11.3 - 35.3)
4a	1.8 (0.8 - 2.7)	9.6 (5.2 - 13.0)	26.4 (12.8 - 39.5)
4b	1.9 (0.9 - 2.8)	10.0 (5.4 - 13.5)	27.1 (13.2 - 40.6)
Broken-stick	1999	2003	2001
Scenario 2	0 (0 - 0)	5.6 (1.9 - 8.6)	11.4 (3.6 - 19.2)
3a	0 (0 - 0)	7.4 (2.6 - 11.3)	15.9 (5.0 - 26.5)
3b	0 (0 - 0)	9.0 (3.2 - 13.6)	20.1 (6.5 - 33.2)
3c	0 (0 - 0)	7.9 (2.8 - 12.0)	17.1 (5.5 - 28.5)
3d	0 (0 - 0)	9.5 (3.4 - 14.2)	21.2 (6.9 - 34.9)
4a	0 (0 - 0)	10.8 (3.9 - 15.9)	25.4 (8.3 - 41.0)
4b	0 (0 - 0)	11.0 (4.0 - 16.2)	26.4 (8.7 - 42.6)

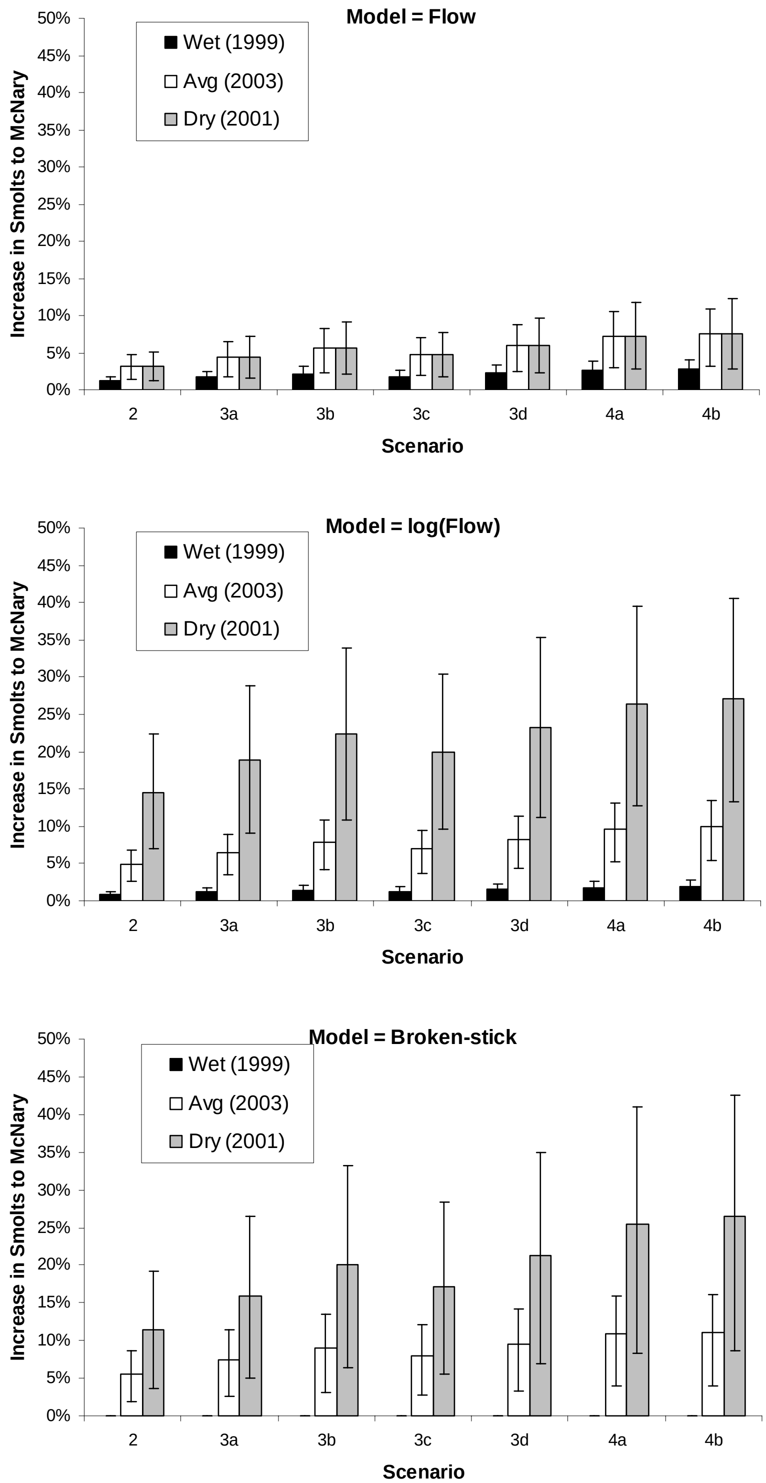


Figure 28. **Estimates of the percent increase in the number of coho smolts surviving to McNary as a result of anticipated flow increases for each flow scenario. Error bars indicate approximate 95% prediction intervals based on intervals for flow coefficients.**

4.3.5. Effects of flow increases on adult returns

Estimated increases in coho adult abundance based on “model averaging” are shown in Table 24, while estimates for each form of the flow-survival relationship are shown in Table 25. The AIC weights (w_i) used in model averaging were 0.34, 0.65, and 0.01 for the *flow*, *log(flow)*, and broken-stick forms, respectively. Thus, abundance estimates were heavily weighted toward estimates for the *log(flow)* model, which had the strongest support based on AIC, though the *flow* model also received considerable weight..

For model averaging, estimates of proportional increases in adult abundance ranged from roughly 5% to 9% for the “historic” frequency of future year types (“25/25/50” or 25% wet, 25% dry, and 50% average years), and from 7% to 14% for the pessimistic assumption (“50/50” or 50% dry and 50% average years) (Table 24). Depending on the scenario, numeric increases ranged from only 50 to 140 adults when based on an expected return equal to the recent 15-year geometric mean, and from roughly 104 to 287 adults given the EDT Restoration abundance (Table 24). Adult estimates were roughly 40% higher under the pessimistic assumption (“50/50”) for future year types.

Estimates specific to each flow-survival relationship (Table 25) highlight the inconsistencies between the two models, *flow* and *log(flow)*, that have similar support based on AIC. Estimates for the *log(flow)* model were generally double those of the *flow* model. In fact, the approximate 95% confidence intervals for these two models often do not overlap (though these intervals must be interpreted with extreme caution, as discussed for fall Chinook).

Table 24. Estimates of average annual increases in coho adult abundance based on “model averaging.” Results are shown for each flow scenario and two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). N = expected annual abundance (geometric mean) given unadjusted flow conditions.

	Percent (%) increase		Numeric increase based on 15-yr mean		Numeric increase based on EDT Restoration	
Scenario	25/25/50	50/50	25/25/50 (N = 1,095)	50/50 (N = 989)	25/25/50 (N = 2,256)	50/50 (N = 2,038)
2	4.6	7.1	50	70	104	145
3a	6.1	9.4	67	93	137	191
3b	7.4	11.3	81	112	167	230
3c	6.5	9.9	71	98	146	202
3d	7.8	11.8	85	117	175	241
4a	9.0	13.6	99	135	203	278
4b	9.3	14.1	102	140	210	287

Table 25. Estimates of average annual increases in coho adult abundance for each flow scenario and flow-survival relationship (*flow*, *log(flow)*, and broken-stick forms). Results are shown for two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). Ranges in brackets are approximate 95% prediction intervals based on smolt estimates. N = expected annual abundance (geometric mean) given unadjusted flow conditions.

Flow	Percent (%) increase		Numeric increase based on 15-yr mean (N = 1,095)		Numeric increase based on EDT Restoration (N = 2,256)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 996)	25/25/50	50/50 (N = 2,051)
2	2.6 (1.0 – 3.9)	3.2 (1.2 - 4.9)	28 (11 - 43)	32 (12 - 49)	58 (23 - 89)	65 (26 - 100)
3a	3.6 (1.5 – 5.4)	4.4 (1.7 - 6.8)	39 (16 - 60)	44 (17 - 68)	81 (33 - 123)	91 (36 - 139)
3b	4.6 (1.8 – 6.9)	5.6 (2.2 - 8.6)	50 (20 - 75)	56 (22 - 86)	103 (42 - 155)	115 (46 - 177)
3c	3.9 (1.6 – 5.9)	4.8 (1.9 - 7.3)	43 (17 - 64)	48 (19 - 73)	88 (35 - 132)	98 (39 - 150)
3d	4.8 (2.0 – 7.3)	6.0 (2.4 - 9.1)	53 (22 - 80)	59 (24 - 91)	109 (44 - 164)	122 (49 - 187)
4a	5.8 (2.4 – 8.7)	7.2 (2.9 – 11.0)	64 (26 - 96)	72 (29 - 109)	132 (54 - 197)	148 (59 - 226)
4b	6.1 (2.5 – 9.1)	7.6 (3.0 - 11.5)	67 (27 - 100)	75 (30 - 114)	138 (56 - 206)	155 (62 - 236)

Log(Flow)	Percent (%) increase		Numeric increase based on 15-yr mean (N = 1,095)		Numeric increase based on EDT Restoration (N = 2,256)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 985)	25/25/50	50/50 (N = 2,030)
2	5.6 (2.8 - 8.2)	9.2 (4.6 - 13.4)	62 (31 - 90)	90 (46 - 132)	127 (64 - 185)	186 (94 - 272)
3a	7.4 (3.7 - 10.7)	12.0 (6.1 - 17.3)	81 (41 - 117)	118 (60 - 171)	167 (85 - 240)	243 (123 - 352)
3b	8.9 (4.5 - 12.7)	14.3 (7.3 - 20.6)	97 (50 - 139)	141 (72 - 203)	200 (102 - 287)	290 (148 - 417)
3c	7.8 (4.0 - 11.3)	12.7 (6.4 - 18.3)	86 (44 - 124)	125 (63 - 180)	177 (90 - 254)	257 (130 - 371)
3d	9.3 (4.8 - 13.3)	14.9 (7.6 - 21.4)	102 (52 - 145)	147 (75 - 211)	209 (107 - 299)	303 (155 - 434)
4a	10.6 (5.5 - 15.1)	17.0 (8.7 - 24.2)	117 (60 - 165)	168 (86 - 238)	240 (124 - 340)	345 (178 - 491)
4b	11.0 (5.7 - 15.5)	17.5 (9.0 - 24.9)	120 (62 - 170)	173 (89 - 245)	248 (128 - 351)	356 (184 - 505)

Broken-stick	Percent (%) increase		Numeric increase based on 15-yr mean (N = 1,095)		Numeric increase based on EDT Restoration (N = 2,256)	
Scenario	25/25/50	50/50	25/25/50	50/50 (N = 991)	25/25/50	50/50 (N = 2,041)
2	5.1 (1.7 - 8.1)	8.2 (2.7 - 13.1)	56 (19 - 89)	81 (27 - 130)	115 (38 - 184)	166 (55 - 267)
3a	6.9 (2.3 - 10.9)	11.2 (3.8 - 17.7)	76 (26 - 120)	111 (37 - 176)	156 (53 - 247)	228 (77 - 362)
3b	8.6 (2.9 - 13.4)	14.0 (4.8 - 21.8)	94 (32 - 146)	138 (47 - 216)	194 (66 - 302)	285 (97 - 445)
3c	7.4 (2.5 - 11.7)	12.0 (4.0 - 18.9)	81 (27 - 128)	119 (40 - 188)	167 (56 - 263)	245 (83 - 386)
3d	9.0 (3.1 – 14.0)	14.7 (5.0- 22.9)	99 (34 - 153)	146 (50 - 227)	204 (70 - 316)	300 (103 - 467)
4a	10.6 (3.7 - 16.1)	17.3 (6.0 - 26.5)	116 (40 - 176)	172 (59 - 262)	238 (83 - 363)	353 (122 - 541)
4b	10.9 (3.8 - 16.5)	17.9 (6.2 - 27.3)	119 (41 - 181)	178 (62 - 271)	246 (85 - 373)	366 (127 - 557)

4.4. Effects of flow increases on adult returns of steelhead

Example estimates of average annual increases in adult returns for steelhead are shown in Table 26. These estimates were based on flow-survival relationships and model averaging for spring Chinook, and hence, estimates of proportional increases are identical to those in Table 10. Under these assumptions, numeric increases for steelhead ranged from 26 to 71 adults, depending on the scenario and given an expected return equal to the recent 15-year geometric mean. As for spring Chinook, increases in adults were only marginally greater under the pessimistic assumption that future flow conditions would be characterized by 50% dry years and 50% average years (denoted "50/50" in Table 26).

Table 26. Example estimates of average annual increases in steelhead adult returns based on flow-survival relationships and "model averaging" results for spring Chinook. Results are shown for each flow scenario and two hypothetical frequencies of future year types: (1) 25% wet, 25% dry, and 50% average (25/25/50) and (2) 50% dry and 50% average (50/50). N = expected annual abundance (geometric mean) given unadjusted flow conditions.

	Percent (%) increase		Numeric increase based on 15-yr mean	
Scenario	25/25/50	50/50	25/25/50 (N = 1,410)	50/50 (N = 1,308)
2	1.8	2.3	26	30
3a	2.5	3.2	36	42
3b	3.2	4.0	45	53
3c	2.7	3.4	39	45
3d	3.4	4.3	48	56
4a	4.1	5.2	58	68
4b	4.3	5.4	60	71

5.0 Discussion

Our results suggest that flow has a strong effect on Prosser-to-McNary survival rates of fall Chinook, an intermediate effect for coho, and a minimal effect for spring Chinook. These results are similar to those of Neeley (2002), who examined only three years of data (1999-2001). In addition, we found consistent relationships between survival rates and the variables year, day of migration, and travel time for spring Chinook, fall Chinook and coho. In each case, later migrations and longer travel times were associated with lower survival rates. As well, year-specific coefficients indicated a general decline in survival from 2001 to 2004 in all three cases. The consistency of these other relationships is encouraging as it indicates that the survival-rate estimates we examined may be quite informative with respect to flow-survival relationships. On the other hand, there was considerable unexplained variation in survival, especially for spring Chinook and coho, suggesting that key variables were missing form these models.

Commensurate with flow-survival relationships, estimated increases in smolts and adult abundances resulting from flow increases were relatively high for fall Chinook, intermediate for coho, and minimal for spring Chinook. Unfortunately, we consider the precision (reliability) of these estimates to be poor, in particular those for adult returns. In the following sections we discuss several caveats and limitations of our results that contribute to the suspect quality of these estimates.

5.1. Uncertainty in flow-survival relationships

Despite promising results, there was considerable uncertainty about each estimated flow-survival relationship, as well as uncertainty about the appropriate form of that relationship (*flow*, *log(flow)*, or broken-stick forms). In fact, the "best" form differed in each case. On one hand, such differences in results among spring Chinook, fall Chinook, and coho are not too surprising because (1) the number of survival-rate estimates differed greatly among them, and (2) their responses to flow conditions might be expected to differ given general differences in their size, behavior, and timing of out-migration. However, there is considerable ambiguity when different forms of the flow-survival relationship have similar statistical support but lead to quite different estimates of potential benefits of flow increases. This discrepancy was most obvious for coho salmon. The *flow* and *log(flow)* forms had similar support in this case, but estimates of increases in smolts to McNary were roughly four times greater for *log(flow)* than *flow* for the "dry" year (2001).

In addition, flow-survival relationships for both fall Chinook and coho weakened considerably when the variable *year* was removed from regression models, largely because of dependencies among flow coefficients and those for 2001. Flow-survival relationships with *year* removed roughly corresponded to the lower confidence intervals of relationships estimated for the "full" models. In general, strong flow-survival relationships were not consistent with observed survival-rate estimates for 2001. This is visually apparent in the data plots for spring Chinook, fall Chinook, and coho. In each case, numerous release groups passed Prosser when flows were between 500 and 1000 cfs, but their survival rates were similar to, or greater than, those observed for 2002 to 2004.

We modeled all years of data simultaneously in an attempt to generalize flow-survival relationships that would be potentially applicable future years, and included *year* as a candidate variable to account for potential differences in mean survival rates among years that could not be accounted for by other variables. An obvious mechanism giving rise to such effects would be year-to-year differences in the abundance and/or distribution of predators. In 2001, juveniles passing Prosser, in particular spring and fall Chinook smolts, were generally larger than in other years. In addition, mortality of spring Chinook juveniles prior to reaching Prosser was apparently much higher in 2001 than in other years (Neeley 2004). One might therefore hypothesize that survival rates from Prosser-to-McNary were relatively high in 2001 because migrants were larger and/or better suited for survival. On the other hand, if 2001 data accurately reflect a weak relationship between flow and survival, then it implies that (moderately) low flows did not contribute to the poor survival rates for fall Chinook and coho observed in 2004, for example.

Unfortunately, it is difficult to distinguish among these hypotheses because (1) key factors such as predator abundance are unknown, and (2) survival-rate estimates for a given year are essentially “pseudo-replicates.” Moreover, our models were limited to six or seven years of data, with 2001 being the only year exhibiting extreme low-flow conditions.

The assumption that steelhead smolts were comparable to Chinook salmon smolts in terms of a flow-survival relationship was also questionable. There is no evidence that steelhead and Chinook react in comparable manners to flow or other environmental variables in the Yakima River. This assumption was made out of necessity to provide some level of analysis. Although we use actual steelhead smolt emigration data, the statistical relationships we developed to quantify the impacts of flow on steelhead were derived from our analysis of Chinook salmon emigration trends. Thus, not only is the flow-survival relationships highly uncertain due to inherent limitations of the statistical analysis, but there is an additional level of uncertainty associated with the assumption that steelhead are comparable to Chinook salmon.

In sum, estimates of flow-survival relationships and increases in smolts to McNary are highly uncertain and potentially misleading. While other analytical methods could be used to further explore these relationships (e.g., hierarchal models or separate year-specific comparisons), it is unlikely that more precise relationships can be derived or reliably extrapolated to future years without additional data for low-flow conditions.

5.2. Uncertainties in Adult Estimates

Estimates of proportional and numeric increases in adult returns were highly speculative. Uncertainties in these estimates stem not only from uncertainties in smolt estimates, but also from the assumed link between smolt and adult production. To reiterate, estimates for adult returns represented annual averages across a hypothetical set of future years. We first assumed an average value for returns across years under baseline (unadjusted) flow conditions, and then scaled this value by the proportional increases in smolts surviving to McNary estimated for each alternative flow scenario. By doing so, we implicitly assumed that both smolt passage at Prosser and McNary-to-Prosser SAR values were the same for all year types, or similarly, that the product of these two components was the same for all year types.

Our assumption that adult increases would be directly proportional to smolt increases is unsupported. Any within-population competitive interactions (density-dependence) among smolts would result in less-than-proportional increases in adults. Further, an assumption underlying a proportional increase is that an individual's probability of survival during one stage of migration is independent of that for subsequent life stages. Though speculative, it seems more plausible that individuals that avoid predation from Prosser to McNary because of an increase in flow would be more likely on average to suffer subsequent mortality, again implying a less-than-proportional increases in adults. On the other hand, if increases in flows reduced travel times and/or energy expenditures of all individuals (including those that would have survived regardless of flow increases), then survival probabilities beyond McNary might also be increased, resulting in more-than-proportional increases in adult returns.

There is, however, evidence to suggest that smolt passage and/or McNary-to-Prosser SAR values differ between the general "year types" that characterize flow conditions during out-migration. For example, Neeley (2004) found that survival rates from Roza Dam to McNary Dam, as well those after McNary passage, were much lower for spring Chinook in 2001 (dry year) than in other years. SAR values for coho in 2001 were also extremely low compared to adjacent years (Bosch et al. in review). In contrast, strong runs of all species in recent years coincided with "wet" years for out-migration conditions. To the extent that smolt production and/or McNary-to-Prosser SAR values are lower on average for "dry" years than for "wet" or "average" years, estimates of adult benefits will be biased high (overstated). This is because expected adult returns will be lower on average in dry years than we assumed, and hence, numeric increases in adults will be lower as well.

As with the flow-survival relationships, changes in adult steelhead returns are founded on changes in emigration success of juveniles, which in turn are founded upon the assumption that Chinook are a suitable surrogate for steelhead. This assumption is unsupported and was made in order to provide some analysis. Therefore, additional skepticism of our results pertaining to steelhead is warranted.

Finally, we used “model averaging” as a simple means of accounting for uncertainty in the form of the flow-survival relationship when computing adult estimates. However, as noted above, different forms often had similar statistical but gave divergent estimates of benefits. Thus, estimates based on any one form as well as those for model averaging should be interpreted cautiously.

5.3 Summary

The relationships described in this report reflect the complex nature of smolt survival and environmental variables. In some cases, the finding that flow was an important variable in estimating survival mirrors results reported in the Snake and Columbia River (Sims and Ossiander 1981, Cada et al. 1997, Giorgi et al. 2002). Other studies seem to indicate that flow may be less important (Anderson et al. in press). Our study is somewhat unique in that it was completed in a much smaller river than the Snake or Columbia. Our conclusion that the nature and strength of the flow survival relationship depends on the species or fish stock may reflect the smaller size of the Yakima River, and the more natural geomorphology in comparison to the Snake and Columbia Rivers.

Although the Yakima River has a highly modified hydrograph, it is still by and large a free flowing river with the attendant hydraulic cues that are thought to guide smolt emigration (Goodwin et al. 2004). By comparison, the Snake and Columbia Rivers have a higher prevalence of reservoirs that do not reflect a natural geomorphic condition. Thus, even though the Yakima River may be highly regulated, it still retains a geomorphic based series of hydraulic queues that may increase or decrease in strength as flow changes in a manner typical of a natural river. Flow may therefore be more important in the Yakima River than in the Columbia and Snake Rivers.

As previously noted, the relationship between flow and survival varied depending on the species and stock. The reason for this is unknown, and it is a primary indication of the lack of understanding that is attainable with our approach to estimating the impacts of flow alteration on smolt emigration and survival. We examined several empirical relationships between flow and survival, though we did not link our findings with plausible physical explanations. To account for such uncertainty, we averaged our findings across alternative flow-survival relationships and weighted them to reflect their relative statistical support. Conceptually, however, the general shape of the flow-survival relationship should be similar for all emigrating salmonids, even though the strength of the relationship may differ because of species or stock-specific attributes such size, migration timing, and habitat occupancy behaviors.

Implementation of any of the pump-exchange alternatives will have the potential to increase survival of emigrating salmonids in the lower Yakima River. Increased flow, however, is not a guarantee of improved migration conditions. Therefore, we urge continued monitoring and additional research in order to gain further understanding about what environmental variables are really driving emigration success in the lower Yakima River.

6.0 References Cited

Anderson, J.J. E. Gurarie, and R.W. Zabel. Mean free-path theory of predator-prey interactions: application to juvenile salmon migration. Ecological Modeling (in press).

Bosch, W.J., T.H. Newsome, J.L. Dunnigan, J.D. Hubble, D. Neeley, D.T. Lind, D.E. Fast, L.L. Lamebull, and J.W. Blodgett. Evaluating the feasibility of reestablishing a coho salmon population in the Yakima River, Washington. North American Journal of Fisheries Management (in review).

Burnham, K.P. and Anderson, D.R., 2002. Model selection and multimodel inference: A practical information-theoretic approach. Springer-Verlag, New York.

Cada, G.F., Deacon, M.D., Mitz, S.V., and Bevelhimer, M.S. 1997. Effects of water velocity on the survival of downstream-migrating juvenile salmon and steelhead: a review with emphasis on the Columbia River Basin, Reviews in Fisheries Science 5(2): 131-183.

Dobson, A.J. 2002. An Introduction to Generalized Linear Models (second edition). Chapman and Hall, London.

Goodwin, R. A., Nestler, J. M., Anderson, J. J., and Weber, L. J. (2004). "Virtual fish to evaluate bypass structures for endangeredspecies." *Proceedings of the 5th International Symposium on Ecohydraulics*, 12 – 17 September 2004, Madrid, Spain.

Leung, L.R., Y. Qian, X. Bian, W.M. Washington, J. Han, and J.O. Roads. 2004. Mid-century ensemble regional climatic change scenarios for the western United States. Climate Change 62: 75-113.

McCullagh, P. and Nelder, J.A. 1989. Generalized Linear Models (second edition), Chapman and Hall, London.

Mote, P.W., E.A. Parson, A.F. Hamlet, W.S. Keeton, D. Lettenmaier, N. Mantua, E.L. Miles, D.W. Peterson, D.L. Peterson, R. Slaughter, and A.K. Snover. 2003. Preparing for climatic change: the water, salmon, and forest of the Pacific Northwest. Climatic Change 61: 45-88.

Neeley, Doug. 2002.Comparison of Prosser-Dam-to-McNary Dam Smolt Survival over Yakima Flow Intervals for 1999, 2000, 2001 Spring Chinook, Coho, and Fall Chinook Emigrants. International Statistical Training and Technical Services. Oregon City, Oregon.

Neeley, D. 2004. Appendix C: OCT-SNT Survival. *In* Bosch, B., D. Fast, and M. R. Sampson. 2004. Yakima Klickitat Fisheries Project Monitoring and Evaluation Final Report. Prepared for the Bonneville Power Administration.

Payne, J.T., A.W. Wood, A.F. Hamlet, R.N. Palmer, and D.P. Lettenmaier. 2004. Mitagating the effects of climate change on the water resources of the Columbia River basin. Climatic Change 62: 233-256.

Sanford, B.P., and S.G Smith. 2002. Estimation of smolt-to-adult return percentages for Snake River Basin anadromous salmonids, 1990-1997. J. Agric.Biol. Environ. Stat. 7:243-263

Sims, C. and Ossiander, F. 1981. Migrations of juvenile Chinook salmon and steelhead in the Snake River, from 1973-1979, a research summary. U.S. Army Corps of Engineers

Venables, W.N. and Ripley, B.D.1999. Modern Applied Statistics with S-PLUS. Springer-Verlag, New York.

Washington State Department of Ecology (WDOE). 2001. USBR Columbia River pump exchange project potential water quality impacts on the lower Yakima River. 01-03-000.