DSM TN 55. Projecting management success using a fitted life cycle model and simulated management action

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Introduction

The starting point for this exercise was the fitted Delta Smelt Life Cycle Model with explicit modeling of entrainment (LCME; Smith et al. 2021). LCME quantified the relationship between ecosystem conditions and delta smelt reproductive and mortality rates, using 21 years of abundance, entrainment, and ecosystem covariate information. The best set of covariates for delta smelt vital rates was identified by Polansky et al. (2021) and included average March-April water temperature, the sum of June-August *Outflow*, average Old and Middle River flow (*OMR*), average water transparency in the south Delta (a measure of South Delta Turbidity), and summer and winter food web conditions. Though Outflow was selected as a summer covariate, it was consider a multivariate index of several ecosystem conditions including temperature and food web. LCME leveraged the results of Polansky et al. (2021) to identify the best set of covariates, while separately estimating two sources of delta smelt mortality: entrainment and natural mortality. Following IEP MAST (2015), OMR and South Delta Turbidity were assumed to be entrainment mortality covariates for all affected life stages (December-June); March-April water temperature was assumed as a recruitment covariate, and all others (Outflow, fall Delta-wide turbidity, winter striped bass abundance, and winter food availability) were assumed to be natural mortality covariates.

A simulation model to project growth of the delta smelt population under future, managed Delta ecosystem conditions was integrated with LCME in order to predict the probability of successfully growing the population, under a range of potential conditions. The projection model with a few simple examples was documented by Smith et al. (2021). Here, the projection model is modified to simulate population supplementation with hatchery-origin fish, and an improved model to simulate future covariates, representing ecosystem conditions, is developed.

Methods

The Delta Smelt Life Cycle Model was fit using Bayesian methods, which facilitate an accounting of several sources of uncertainty. Bayesian models are often fit using Markov Chain Monte Carlo

simulation methods that can be easily modified to simulate future, or projected populations, given some assumption about ecosystem conditions (e.g., management actions). LCME model projections accounted for three sources of uncertainty: parameter uncertainty, process variation, and covariate uncertainty. Parameter uncertainty is the precision at which a model parameter is estimated. Process variation is the difference between the expected population response to an environmental change and the actual response, and covariate uncertainty captures randomness in future ecosystem conditions. Parameter uncertainty and process variation were addressed using the state model described below, and covariate uncertainty was addressed by integrating the state model with the covariate model described below.

State model

The dynamic equations of the state model were defined by Smith et al. (2021), but are succinctly redefined here for convenience. LCME modeled latent abundance dynamics for the early post-larvae ($n_{\rm AB_{PL1c}}$), late post-larvae ($n_{\rm AB_{PL2c}}$), juveniles ($n_{\rm AB_{Jc}}$), early sub-adults ($n_{\rm AB_{SA2c}}$), late sub-adults ($n_{\rm AB_{SA2c}}$), early adults ($n_{\rm AB_{A1c}}$), and late adults ($n_{\rm AB_{A2c}}$).

(1)
$$n_{AB_{sc}} = \begin{cases} SSB_{A1(c-1)} * \rho_{1c} & \text{for s = PL1} \\ n_{AB_{PL1c}} * \varphi_{PL1c} + SSB_{A2(c-1)} * \rho_{2c} & \text{for s = PL2} \\ n_{AB_{(s-1)c}} * \varphi_{(s-1)c} & \text{for s = J, SA1, SA2, A1 and A2} \end{cases}$$

where $\rho_{\rm sc}$ and $\varphi_{\rm sc}$ were life stage s and cohort c specific recruitment and survival functions, respectively, and the spawning stock biomass $(SSB_{\rm sc})$ depended on adult abundance and mean fork length $FL_{\rm sc}$ converted to weight $(SSB_{\rm sc} = 0.5*n_{\rm AB_{sc}}*1.8*10^{-6}*FL_{\rm sc}^{3.38}$ [Kimmerer et al. 2005]). Reproductive success rates $\rho_{\rm sc}$ were modeled using lognormal distributions. Reproduction by early adults was modeled with an overall log mean α_0 , and reproductive rate of late adults was a function of α_0 and mean April-May water temperature $X_{\rm Rc}$,

(2)
$$\rho_{sc} \sim \text{Lognormal} \begin{pmatrix} \alpha_0, \sigma_R \\ \alpha_0 + \alpha_1 * X_{R_c}, \sigma_R \end{pmatrix} \text{ for } s = \text{PL1}.$$

The survival functions φ_{sc} explicitly described instantaneous rates of natural mortality M_{sc} and entrainment mortality F_{sc} , when entrainment occurred (s=PL1, PL2, SA1, SA2, A1), as simultaneous, competing sources of mortality,

$$(3) \varphi_{\rm sc} = e^{-(F_{\rm sc} + M_{\rm sc})}$$

and fixed $F_{sc} = 0$ for life stages when no entrainment was observed (s=J).

M was modeled as a lognormal random variable whose expectation depended on a single covariate per life stage transition $X_{M_{isc}}$ (Table 1) and parameters β ,

(4)
$$M_{sc} \sim \text{Lognormal} \left(\left(\beta_0 + \beta_1 * W_s + \beta_{s+1} * X_{M_{sc}} \right), \sigma_{M_s} \right).$$

The quantity $\beta_0 + \beta_1 * W_s$ represented a stage-specific intercept, informed by expected mean weight W_s , and the quantity $\beta_{s+1} * X_{M_{sc}}$ represented annual deviations from the stage-specific mean, informed by covariate $X_{M_{sc}}$ (Table 1).

F was also modeled as a lognormal random variable with expectation that depended on Old and Middle River flow (*OMR*), South Delta Turbidity, and the interaction of the two, represented as covariate matrix $X_{F_{sc}}$

(5)
$$F_{sc} \sim \text{Lognormal}\left(\left(\gamma_{0,s} + \sum_{i=1}^{3} \gamma_{is} * X_{F_{sc}}\right), \sigma_{F_{s}}\right)$$

Covariate model

In order to develop the best possible representation of future environmental conditions, it was important to account for any multivariate relationships among the LCME covariates (X_{R_c} , X_{F_s} , and X_{M_s}) used for making model predictions, and to avoid simulated X far out of the range of observed X. Multivariate kernel density methods were used to account for possible covariance among X. Kernel density models are a non-parametric approach for estimating probability density functions. The method can be viewed as an extension of the histogram, where the multivariate space is divided into an evenly-spaced grid and then sub-models are fit within each cell of the grid.

In order to reduce the dimensionality of kernel density models, covariates were grouped *a priori* into three groups, representing spring through fall conditions, winter abiotic conditions, and winter biotic conditions (Table 2). Within-group covariance was accounted for by fitting a separate kernel density model to each group; between-group covariance was ignored. Kernel density models were fit using the ks package in R (R 2018), with grid size set to 12.

Joint samples from each kernel model were used to represent future covariate combinations. While most samples were within the range of observed X, some samples were implausible because they were far outside the range of observed values or they represented impossible values, such as negative Secchi depths. Joint samples including implausible simulated covariate values were rejected and replaced with new joint samples. Among all X_{R_c} , X_{F_s} , and X_{M_s} , simulated X less than 75% of the minimum observed X or more than 125% of the maximum observed X were rejected and replaced with new joint samples of the multivariate kernel density model.

New simulated covariates were sub-sampled from the total sample using two criteria reflecting two assumptions about future Delta conditions. Under the first assumption, the future would resemble the entire time series, from 1995-2015, including several years of cool springs, very low *OMR*, and occasional high summer *Outflow*. Under the second assumption, the future would

resemble the latter half of the time series, during 2005-2015, with warmer spring temperatures, *OMR* controlled at more than -5,000 cfs, and lower summer *Outflow*.

Projection model

New random values for recruitment (ρ_{sc} ; Eq. 2) and mortality (M_{sc} and F_{sc} ; Eq. 4-5) were simulated for each life stage and cohort year using joint posterior samples of model parameters (α , β , γ and σ) and simulated covariate values to generate expected vital rate values. That is, random values of α , β , γ and σ and random values of X_{R_c} , X_{M_s} , and X_{M_s} , described above, were substituted in Eqs. 1-5 to project the simulated population forwards two, five, or ten years.

Entrainment projection. Entrainment actions were simulated by changing the distribution of OMR values. OMR was changed in two ways. In the first approach, all OMR values simulated from the kernel density models that were less than a certain value were rejected and replaced with another value (e.g., reject OMR < 0 ft³/s and replace with OMR = 0 ft³/s). This approach broke the covariance structure among covariates accounted by the kernel density model, but it allowed a representation of extreme conditions that were rarely observed. In the second approach, all joint samples with an OMR less than some critical value were rejected and replaced with new simulated joint samples of all covariates. This approach preserved the covariance structure among covariates, but as more joint samples with lower OMR were rejected, the distributions of other covariates were affected. For example, higher spring OMR are associated with cooler springs and higher outflow summers, which result in greater modeled reproductive success and lower summer natural mortality.

Supplementation projection. Supplementation actions were simulated by adding $n_{SP_{sc}}$ supplemented fish to the abundances in Eq. 1, that survived at rate ψ_{sc} during the time period after stocking. For example, simulated supplementation of the A1 (early adult life stage, at the end of February) modified Eq. 1 such that

(6)
$$n_{AB_{A1c}} = n_{AB_{SA2c}} * \varphi_{SA2c} + n_{SP_{A1c}} * \psi_{A1c}$$

 $\psi_{\rm sc}$ were an unknown quantity, so uncertainty in this parameter was addressed by sampling a new ψ from an assumed distribution (Uniform(0.25,0.75)), at each iteration of the simulation. In this example, ψ varied among simulations, but not among years within a single simulation. Future data from caging studies may be used to develop a better estimate of ψ and quantify the sources of variation in ψ .

LCME did not model eggs, but it did model the success rate of spawners, producing postlarvae that recruited in June. This reproductive success rate ρ_{sc} (Eq. 2) accounted for several recruitment processes including hatching rate and survival across several larval life stages. Supplementation

of eggs was simulated by converting a number of supplemented eggs $n_{\rm egg}$ to adult equivalents $n_{\rm EQ_{sc}}$, using the length-fecundity model estimated by Damon et al. (2016)

(7)
$$n_{\text{EQA1,c}} = \frac{n_{\text{egg}}}{0.0183*FL_{\text{Sc}}^{2.7123}}.$$

 $n_{\rm EQ_{s,c}}$ represented eggs that skipped the survival process of stocked adults accounted by ψ , and the survival related to entrainment and natural mortality of wild adults, accounted by φ . FL was used to estimate both $n_{\rm EQ_{A1,c}}$ from $n_{\rm egg}$ (Eq. 7) and the average weight of $n_{\rm EQ_{A1,c}}$ fish that was then used to convert $n_{\rm EQ_{A1,c}}$ to $SSB_{\rm sc}$. Egg supplementation effects were modeled as the equivalent of wild eggs by assuming FL = 56 mm in February, the observed 2008-2015 average female length, or supplemented eggs could be modeled as having greater hatching success through post-larval survival by assuming FL > 56 mm in February. For this exercise, high quality supplemented adults were 70 mm FL in February, and low quality supplemented adults were 56 mm FL in February.

Simulated management scenarios

All management scenarios were compared to a baseline scenario, representing no change from 1995-2015 or from 2005-2015 environmental conditions, depending on which assumption was made about future conditions. Two alternate entrainment management scenarios were simulated. The first entrainment management scenarios represented more restrictive management by censoring the distribution of *OMR* to no less than 0 ft³ (never negative). The second entrainment management scenario represented the current status quo, as under the 2008 Biological Opinion (BiOp), by restricting *OMR* to the approximate distribution observed during the period under BiOp management, beginning in 2007.

The supplementation scenarios considered (Table 3) were, broadly, stocking of any lifestage from postlarvae to adults during June to February, and supplementation of eggs in March and April. Using a table of current and projected future capacities to produce delta smelt in the hatchery, we developed a range of the number of eggs and later lifestages to explore in simulation. 200,000 to 1,500,000 eggs and 20,000 to 500,000 post-larvae to adults were considered a representative range. Fish or eggs could be the equivalent of wild fish (low reproductive value), or they could have greater success relative to wild fish (high reproductive value). The future environment was assumed to be like the full LCME time series, 1995-2015

Recovery targets and timelines. In order to define the probability of management success in the simulation, it was necessary to define recovery targets and timelines. Success was defined as simulated population growth of the $n_{AB_{A1,c}}$ life stage from the January-February 2021 EDSM abundance estimate of 267 delta smelt (i.e., starting abundance = 267) to a target abundance equal to the 2017 EDSM estimate of 83,787 delta smelt or greater. In other words, target population growth λ_{target} was 83,787/267, or λ_{target} = 313.8. Abundance in 2017 was chosen as a target

because it represented a recent abundance that could be sufficiently measured using the established EDSM program. Success was evaluated at 2-year, 5-year, and 10-year time frames.

Results

A total of 2,500 joint posterior samples of LCME parameters were combined with 25,000 joint samples of covariate kernel densities (10 years x 1,500 samples/year) to generate projections of the delta smelt population. More samples led to memory limitations. Simulated covariates appeared to approximate the covariate values observed during 1995-2015 and 2005-2015, depending on which assumption was made about future conditions (Fig. 1). Truncation of *OMR* distributions at zero (first entrainment management scenario), resulted in a relatively large number of zeros in the simulated dataset and a spike at zero in histograms of the *OMR* distributions (Fig. 2). Rejection of kernel density samples with *OMR* outside the range observed in 2007-2015, the scenario representing entrainment management under the BiOp, resulted in a more narrow distribution of *OMR* in most time periods. The mean differences in simulated *OMR* from the BiOp scenario to the no change scenario were 684 ft³/s, 1731 ft³/s, 837 ft³/s, 1313 ft³/s, and 399 ft³/s for April-May, June, December-January, February, and March, respectively.

Across all management scenarios that were considered, the restriction of simulated covariates to the 2005-2015 distributions resulted in much lower population growth rates, compared to covariates that were like the full 1995-2015 time series (Fig. 3).

Entrainment management scenarios did not result in large differences in population growth from the no change scenario, regardless of which assumption was made about future conditions. Truncation of *OMR* to values greater than or equal to zero did result in positive population growth, but not growth to the target abundance measured in 2017. *OMR* like those observed during 2007 and later, resulted in growth rates near 1 at short time scales but not at longer time scales.

Among supplementation scenarios, simulations in which larger sub-adults and adults were stocked in fall and winter resulted in the highest probabilities that the population would grow to the target abundance (Table 3; Fig. 3). Simulations in which eggs were supplemented in March and April resulted in the lowest probabilities of reaching the target. Differences between stocking large fish (70 mm adults) versus small fish (55 mm adult) were detectable at short time frames (2 years), but not at long time frames (10 years).

Discussion

High process variation makes LCME projections highly uncertain (Fig. 3).

If the future is assumed to be more like recent years, as represented by conditions measured during 2005-2015, the model predicts very low population growth. This is consistent with long-term climate predictions for the region and the decline of delta smelt to near extirpation in the wild since the terminal year of LCM. 2005-2015 conditions were associated with a more limited range of *OMR*, representing greater control over this variable, higher spring temperatures, and lower summer *Outflow*. Collectively, these conditions result in less predicted entrainment than during the past but lower recruitment and over-summer survival due to temperature and *Outflow*. Releasing hatchery-origin fish after summer conditions begin to improve, with lower temperatures and higher outflows in the fall, may be one way to avoid a population bottleneck imposed by high summer mortality.

Among the entrainment management scenarios considered, not even an extremely restrictive *OMR* of no more negative than 0 ft³/s, resulted in a high probability of population growth. Consistent with the findings of Smith et al. (2021), this result suggests that management of more of the Delta environment than just the part related to entrainment (*SDT*, *OMR*, etc.), will be required to restore the delta smelt population.

It was not surprising that adding as many as 750,000 eggs in both March and April did not result in higher population growth. 1,500,000 eggs is only the equivalent of 810 adults of 70 mm FL.

Although we made an assumption for the purpose of this analysis, survival of hatchery fish after stocking ψ is unknown. Likewise, reproductive success of these fish, if they survive, is unknown.

Several single lifestage management scenarios were considered, representing informed guesses at production capacities, but many other scenarios could be considered. Supplementation of any combination of the seven LCME life stages could be simulated, any number of supplemented fish could be explored, alternate future conditions could be simulated, or different survival or reproductive success of supplemented fish could be modeled.

References

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Table 1. Delta smelt life stage transition covariates. Food was the mean carbon-weighted density of adult copepods, Cladocerans, and Mysid shrimp. Acronymns for specific delta smelt surveys are: Spring Midwater Trawl (SMWT), Spring Kodiak Trawl (SKT), 20-mm Survey (20-mm), Summer Townet Survey (TNS), and Fall Midwater Trawl (FMWT).

Life stage and data source	Modeled Rate(s)	Covariates	Covariate aggregate months	Covariate data source		
	Recruitment	Adult abundance	March			
F 1- (1 - 1/DI 1)	Recruitment	Mean adult size	March	SMWT, SKT		
Early post-larval (PL1);	Natural mortality	None.				
May 20-mm	Entroise ant montality	Old and Middle River flow	April-May	USGS		
	Entrainment mortality	South Delta turbidity	April-May	SMWT, SKT and 20-mm		
		Adult abundance	April			
	Recruitment	Mean adult size	April	SKT		
Late post-larval (PL2);		Temperature	April-May	SKT and 20-mm		
June 20-mm	Natural mortality	Outflow	June-August	Dayflow		
	•	Old and Middle River flow	June	USGS		
	Entrainment mortality	South Delta turbidity	June	20-mm and TNS		
Juvenile (J); Jul-Aug TNS	Natural mortality	Delta-wide turbidity	September-November	FMWT		
	NI_61 1.6	Food	December-January	Neomysis/zooplankton surveys		
Early Sub-adult (SA1);	Natural mortality	Age-1+ striped bass	December	FMWT		
Oct-Nov FMWT	E 4 1 4 14-	Old and Middle River flow	December-January	USGS		
	Entrainment mortality	South Delta turbidity	December-January	FMWT, SMWT, SKT		
	NT (1 (1)	Food	February	Neomysis/zooplankton surveys		
Late Sub-adult (SA2);	Natural mortality	Age-1+ striped bass	December	FMWT		
Jan-Feb SMWT and SKT	D	Old and Middle River flow	February	USGS		
	Entrainment mortality	South Delta turbidity	February	SMWT and SKT		
	N. 4- 1 4 124-	Food	March	Neomysis/zooplankton surveys		
Early Adult (A1); March SMWT and SKT	Natural mortality	Age-1+ striped bass	December	FMWT		
	E 4 1 4 4 11	Old and Middle River flow	March	USGS		
	Entrainment mortality	South Delta turbidity	March	SMWT and SKT		
Late Adult (A2); April SKT (after 2001)						

Table 2. Coefficients of determination R^2 of all pairwise groupings of LCME covariates, showing the three groupings that defined three multivariate kernel density models of covariates. Groups = Spting-fall conditions, winter biotic conditions, and winter abiotic conditions. R^2 are color coded, with redder colors indicating pairwise combinations with higher correlation.

	Spring-fall conditions					Winter biotic conditions			Winter abiotic conditions							
	Temp AprMay	Outflow _JunAug	Secchi SepNov	SDSecchi AprMay	OMR AprMar	SDSecchi Jun	OMR Jun	STB1+ Dec	ACM _BPUV _Feb	ACM _BPUV _Mar	SDSecchi DecJan	OMR _DecJan	SDSecchi Feb	OMR _Feb	SDSecchi Mar	OMR _Mar
TempAprMay		0.43	0.16	0.01	0.44	0.01	0.06	0.01	<0.01	<0.01	0.04	0.01	0.01	0.02	<0.01	<0.01
Outflow_JunAug			0.26	0.05	0.64	0.04	0.29	0.1	0.24	0.23	0.04	0.02	0.02	0.04	0.01	0.09
SecchiSepNov				0.66	0.06	0.68	< 0.01	0.26	0.11	0.32	0.31	< 0.01	0.2	<0.01	0.29	<0.01
SDSecchiAprMay					< 0.01	0.89	0.01	0.15	0.15	0.28	0.41	0.02	0.07	<0.01	0.28	0.01
OMR_AprMar						0	0.45	<0.01	0.01	< 0.01	<0.01	< 0.01	0.03	0.01	0.02	0.04
SDSecchiJun							<0.01	0.14	0.11	0.25	0.27	< 0.01	0.10	<0.01	0.33	< 0.01
OMR_Jun								0.04	0.07	< 0.01	0.01	< 0.01	0.01	0.01	0.04	0.01
SBAge1Plus_Dec									0.13	0.07	0.18	0.07	0.21	0.09	0.07	0.02
ACM_BPUV_Fe										0.73	0.15	0.07	0.12	0.09	0.06	0.05
ACM_BPUV_Ma											0.34	0.04	0.25	0.14	0.15	0.11
SDSecchiDecJan												0	0.27	0.11	0.1	0.07
OMR_DecJan													0.03	0.57	<0.01	0.07
SDSecchiFeb														0.14	0.43	0.12
OMR_Feb															0.02	0.45
SDSecchiMar																0.05
OMR_Mar															•	

Table 3. Management scenarios and the associated probability of population growth from the March 2021 to the March 2017 abundance measured by the Enhanced Delta Smelt Monitoring Survey. Population growth was calculated at the end of two-, five-, and ten-year time periods.

	Number of fish stocked	Number		P(growth to March 2017 abundance)						
Scenario		of eggs	Future environment	Low reproductive value			High reproductive value			
		stocked	environment	2-yr	5-yr	10-yr	2-yr	5-yr	10-yr	
No change	0	0	Like 1995-2015	0.0024	0.0804	0.1836				
OMR≥0	0	0	Like 1995-2015	0.0032	0.1308	0.2616				
OMR=BiOp	0	0	Like 1995-2015	0.0020	0.1184	0.2292				
Eggs (March and April)	0	200,000	11 1005 2015	0.0016	0.0988	0.2364	0.0016	0.1076	0.2336	
	0	1,500,000	Like 1995-2015	0.0020	0.1564	0.3068	0.0012	0.1620	0.3196	
- /	20,000	0		0.0012	0.1160	0.2540	0.0028	0.1288	0.3004	
Early	140,000	0		0.0148	0.2028	0.3716	0.0360	0.2656	0.4176	
postlarvae	260,000	0	Like 1995-2015	0.0264	0.2564	0.4020	0.0664	0.3304	0.4660	
(May)	380,000	0		0.0472	0.2860	0.4280	0.0972	0.3744	0.5044	
	500,000	0		0.0628	0.3140	0.4620	0.1092	0.4052	0.5432	
	20,000	0		0.0024	0.1480	0.2872	0.0088	0.1728	0.3448	
Late	140,000	0		0.0404	0.2928	0.4492	0.0880	0.3852	0.4996	
postlarvae	260,000	0	Like 1995-2015	0.0844	0.3732	0.5040	0.1624	0.4392	0.5836	
(June)	380,000	0		0.1100	0.4168	0.5276	0.2084	0.4972	0.6068	
	500,000	0		0.1412	0.4396	0.5572	0.2456	0.5296	0.6360	
	20,000	0		0.0060	0.2012	0.3668	0.0160	0.2592	0.4320	
Juveniles (August)	140,000	0		0.0820	0.4128	0.5548	0.1876	0.5416	0.6156	
	260,000	0	Like 1995-2015	0.1716	0.5168	0.6088	0.3132	0.6168	0.6884	
	380,000	0		0.2460	0.5692	0.6688	0.3804	0.6664	0.7312	
	500,000	0		0.2952	0.6044	0.6860	0.4256	0.7076	0.7480	
	20,000	0		0.0132	0.2660	0.4300	0.0384	0.3624	0.5016	
Early subadults (November)	140,000	0		0.1700	0.5404	0.6496	0.3368	0.6384	0.7180	
	260,000	0	Like 1995-2015	0.3212	0.6344	0.6992	0.4660	0.7328	0.7916	
	380,000	0		0.3876	0.6768	0.7436	0.5416	0.7648	0.8160	
	500,000	0		0.4684	0.7140	0.7764	0.5720	0.7892	0.8348	
	20,000	0		0.0236	0.3444	0.4916	0.0720	0.4384	0.5680	
Late	140,000	0		0.2796	0.6388	0.7108	0.4472	0.7420	0.7972	
subadults	260,000	0	Like 1995-2015	0.4452	0.7204	0.7808	0.5836	0.8092	0.8456	
(February)	380,000	0		0.5120	0.7584	0.8020	0.6552	0.8460	0.8668	
	500,000	0		0.5648	0.7968	0.8424	0.6952	0.8464	0.8840	
	20,000	0		0.0376	0.3888	0.5424	0.1076	0.5132	0.6136	
Early adults (March)	140,000	0		0.3604	0.6912	0.7528	0.5612	0.7924	0.8360	
	260,000	0	Like 1995-2015	0.5136	0.7552	0.8212	0.6704	0.8524	0.8676	
	380,000	0		0.6028	0.8076	0.8480	0.7440	0.8636	0.8916	
	500,000	0		0.6556	0.8384	0.8628	0.7776	0.8812	0.9060	

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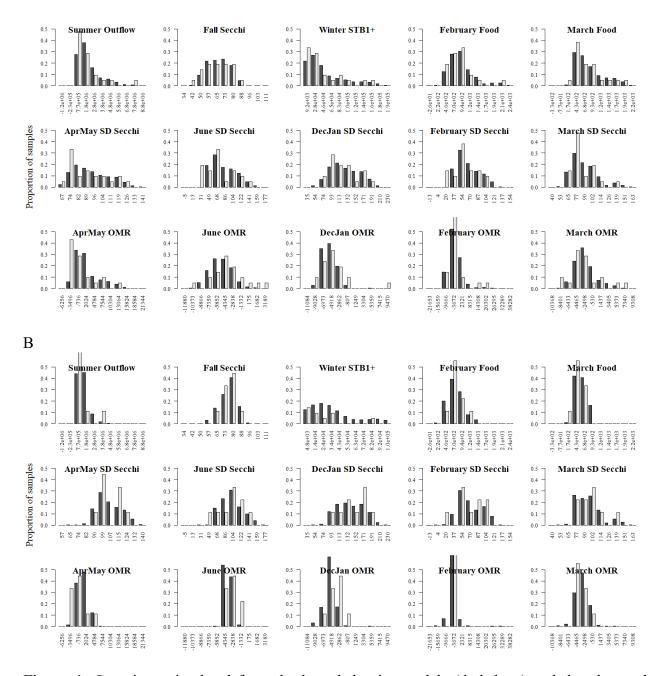


Figure 1. Covariates simulated from the kernel density models (dark bars) and the observed covariate values used to fit LCME (light bars). Each paired histogram represents a set of simulated data and the observed data the simulated data was expected to approximate. The top panel (A) represents conditions simulated to be like 1995-2015, and the bottom panel (B) represents conditions simulated to be like 2005-2015.

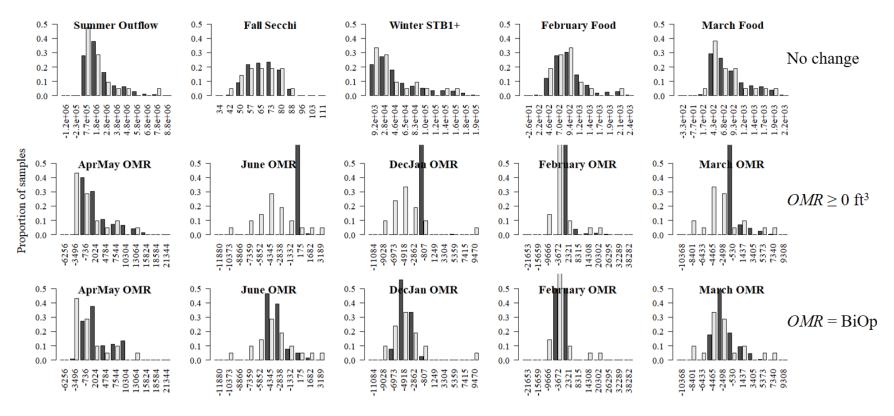


Figure 2. Simulated distribution of Old and Middle River flow (*OMR*) under three entrainment management scenarios (rows). Light bars represent conditions observed during 1995-2015, and dark bars represent simulated conditions.

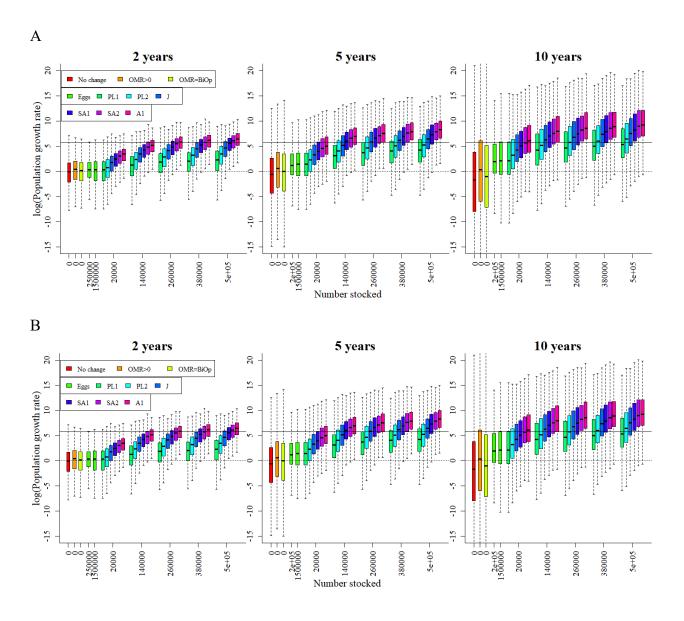


Figure 3. Simulated population growth rates under several example management scenarios, including no change (red), entrainment management (orange and yellow), and supplementation (green to purple boxes). Solid horizontal reference lines indicate the growth rate required to reach the target abundance ($\hat{n}_{AB_{A1,2017}}$ from EDSM of 83,787 delta smelt), and dotted references lines indicate the point between positive and negative projected population growth. The top panel (A) represents simulations with conditions like 1995-2015, and the bottom panel (B) represents simulations with conditions like 2005-2015.

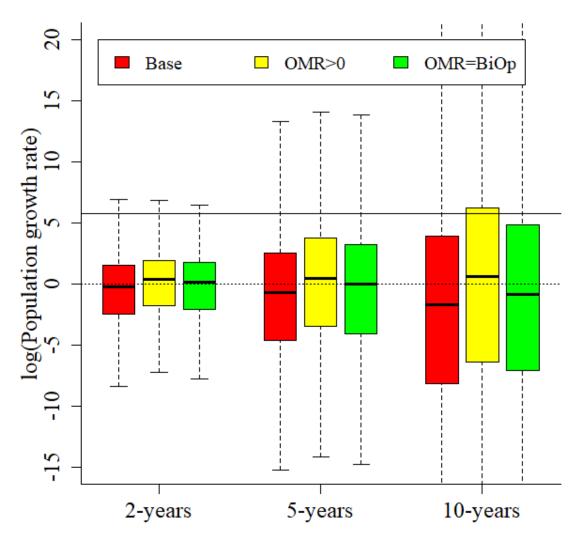


Figure 4. Simulated population growth rates under only entrainment management scenarios. Solid horizontal reference lines indicate the growth rate required to reach the target abundance ($\hat{n}_{AB_{A1,2017}}$ from EDSM of 83,787 delta smelt), and dotted references lines indicate the point between positive and negative projected population growth. Future environmental conditions were assumed to be like 1995-2015.

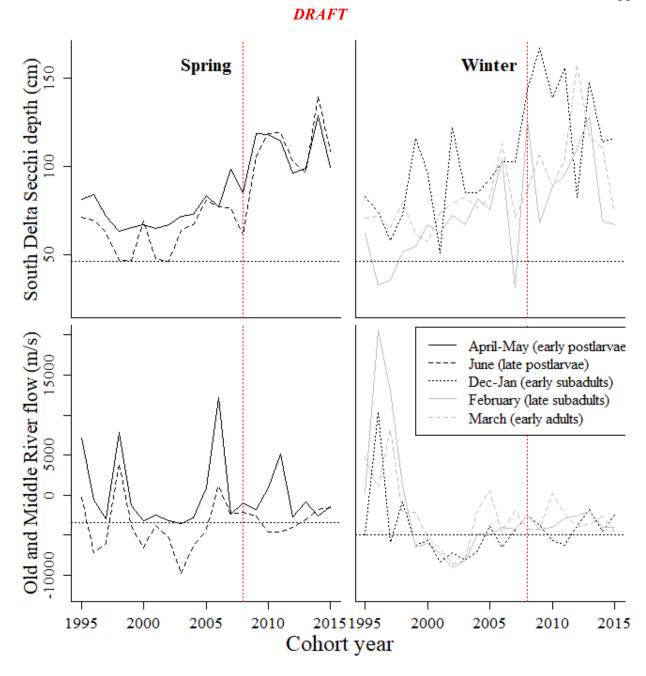


Figure 5. Time series of the South Delta Secchi depths and Old and Middle River flows that were summarized as entrainment covariates and used to fit the Delta Smelt Life Cycle Model. The vertical reference line indicates the year the 2008 Biological Opinion was published, and the horizontal reference lines indicate management thresholds of OMR = -5,000 ft³/s in the winter, OMR = -3,500 ft³/s in the spring, and SDT = 12 NTU (Secchi depth ≈ 47 cm).